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Floods, Public Budgets and Fiscal Resilience: Evidence from Italian Municipalities

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Summary

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Keywords: Fiscal resilience; Hydrogeological disasters; Municipal budgets

JEL Classification: H71, H72, H84, Q54

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Abstract

We examine the impact of extreme hydrogeological events on local governments' fiscal responses in Italy between 2016 and 2022, with a focus on how local public finances contribute to disaster resilience. Leveraging the staggered timing of disaster declarations and employing a difference-in-differences framework, we estimate dynamic treatment effects on revenue and expenditure of municipal governments. Our findings indicate that local governments of affected municipalities significantly increase total and capital expenditures in the aftermath of disasters, particularly in functions related to emergency management, environmental protection and economic development. These spending increases are primarily financed through capital revenues and transfers from higher levels of government, with no corresponding rise in current expenditures. To explore heterogeneity in fiscal responses, we develop a fiscal resilience index combining measures of debt servicing costs and tax autonomy. We find that municipal governments with both low debt burden and high tax autonomy exhibit the strongest and most persistent post-disaster financial adjustments. In contrast, municipal governments with high debt service obligations and limited tax autonomy exhibit weaker responses, reflecting a constrained capacity to mobilize financial resources. These results underscore the critical importance of fiscal space, beyond formal fiscal autonomy, in shaping local governments' ability to respond to climate-related shocks. From a policy perspective, our findings highlight the need to strengthen institutional and financial mechanisms that enhance fiscal resilience and ensure timely access to recovery resources for municipal governments with limited capacity.

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1 Introduction

Climate change poses a growing threat to both environmental and socio-economic systems worldwide (Nordhaus, 2019). According to the European Center for Medium-Range Weather Forecasts (ECMWF, part of the Copernicus Programme), 2024 was the first year with an average global temperature exceeding 1.5°C above the pre-industrial level. These data highlight the accelerating impact of anthropogenic activities on climate (ECMWF, 2025). This effect has been accompanied by an increased frequency and severity of climate-related natural disasters, particularly extreme precipitation events that trigger floods and landslides (AghaKouchak et al., 2020; World Meteorological Organization, 2021).

Hydrogeological events are increasingly affecting urban areas, with uneven spatial impacts. Mediterranean regions (the so-called Mediterranean hotspot) are particularly exposed due to their climatic and geographical features (Llasat et al., 2010; Marchi et al., 2010; Amponsah et al., 2018). Among them, Italy is highly vulnerable owing to its complex orography, patterns of urban development and exposure to extreme weather events (Tropeano and Turconi, 2004; Guida et al., 2016; Esposito et al., 2023). According to the Italian Inventory of Floods and Landslides (*Inventario dei Fenomeni Franosi in Italia, IFFI*) and EM-DAT databases, over 1,000 landslides and 11 major floods struck Italy between 2016 and 2024. Hydrogeological disasters, especially floods, accounted for 41% of all extreme natural events in the period (Guha-Sapir et al., 2013).

The economic consequences of such disasters are far-reaching. They cause destruction of physical capital, disruptions to production and supply chains and widespread wealth and income losses (Hallegatte et al., 2007; Hallegatte and Przyluski, 2010; Cavallo and Noy, 2011; Mohan et al., 2018). Labour income typically declines first, as infrastructure damage disrupts business operations and employment (Reaños, 2021; Jia et al., 2022; Clò et al., 2024). Property values fall, reducing household wealth and long-term investment returns (Leiter et al., 2009; Roy, 2023; Ballocci et al., 2024). These private sector shocks translate into a deterioration of public finances: municipal revenues shrink, just as expenditure needs increase to fund emergency services, infrastructure reconstruction and social assistance (Ouattara and Strobl, 2013; Mohan et al., 2018; Ahmadu and Nukpezah, 2022; Deryugina, 2022).

Local governments are at the frontline of disaster management. They are responsible for immediate response, ensuring continuity of essential services and planning for long-term recovery (Noy and Nualsri, 2011). This requires mobilizing scarce resources and investing in preparedness and resilience (Melecky and Raddatz, 2015; Richert et al., 2019; Fan et al., 2022; Motlagh et al., 2024). However, the capacity to respond varies widely across municipal governments due to differences in fiscal space, institutions and socio-economic conditions.

Understanding this local heterogeneity is critical. Geographic factors, land use, the degree of urbanization and fiscal capacity shape both disaster risk and the ability to respond effectively (Marchi et al., 2010; Lazzaroni and van Bergeijk, 2014; Feng et al., 2021). Governance quality, community networks and social-health aspects also influence how municipal governments prepare for and recover from climate-related shocks (Bosseler et al., 2021).

In this context, the concept of fiscal resilience, defined as the capacity of local governments to absorb, adapt to, and recover from external shocks without compromising long-term financial sustainability, has gained increasing relevance. A growing body of literature highlights that fiscal resilience is closely linked to the availability of fiscal space, understood as the room for manoeuvre to implement discretionary fiscal policy without endangering long-term debt sustainability (Lis and Nickel, 2010; Barbera et al., 2013; Haksar et al., 2018; OECD, 2022). Although fiscal space is a macro-fiscal concept, its importance becomes particularly pronounced in the context of climate-related disasters, where local governments must respond swiftly to emergencies while safeguarding long-term budgetary health. This challenge is especially evident in Europe, where the growing frequency and severity of climate-related events, such as floods, heatwaves and landslides, is compounded by supranational fiscal constraints. In particular, the EU's Stability and Growth Pact poses significant limits on structural deficits and public debt, potentially constraining the capacity of subnational governments to mobilise fiscal responses to exogenous shocks (Zenios, 2022).

While fiscal autonomy, i.e. the ability to raise revenues and allocate expenditures independently, is often seen as a strength, recent evidence suggests that resilience depends more critically on the presence of tangible fiscal buffers. These include a low debt service and timely access to intergovernmental support (Jerch et al., 2023). In the absence of such buffers, municipal governments may face difficult trade-offs in the aftermath of a disaster, such as cutting essential services, deferring infrastructure investments or accumulating unsustainable debt burden (Deria et al., 2020; Deryugina, 2022; Ishida et al., 2023).

This study offers novel insights into the socio-economic and fiscal effects of hydrogeological disasters by analysing how Italian municipal governments responded to floods and landslides between 2016 and 2022. We address two key research questions: (i) how do such disasters affect the composition of the budget of municipal governments, both in terms of revenues and expenditures? and (ii) to what extent does fiscal resilience influence local governments' capacity to respond and to manage disaster-related fiscal risks? To answer these questions, we exploit the staggered timing of officially declared disaster events (*Stati di Emergenza*) caused by hydrogeological hazards and apply the staggered difference-in-differences estimator proposed by Callaway and Sant'Anna (2021), which allows us to estimate dynamic treatment effects over multiple post-disaster years. In addition, we develop an index of fiscal resilience based on two key indicators, debt service costs and tax autonomy, which we use to capture pre-disaster fiscal capacity and assess how differences in fiscal resilience shape the magnitude and persistence of municipal budgetary responses to climate-related shocks.

In addressing these questions, the study contributes to the literature by providing detailed evidence on how local governments in Italy respond to hydrogeological disasters (Morvan, 2024). Applying the municipal budget constraint framework and exploiting granular fiscal data, we assess both the magnitude and composition of post-disaster budget adjustments, while explicitly accounting for differences in pre-disaster fiscal capacity (Jerch et al., 2023). In contrast to earlier work, such as Lodi et al. (2023), our analysis covers the universe of Italian municipalities and spans a broader time horizon, thereby enhancing the generalizability and external validity of our findings.

Our results show that hydrogeological events lead to substantial increases in total and capital expenditures, particularly in key areas such as emergency management, environmental protection and economic development. These spending increases are largely financed through capital revenues and intergovernmental transfers, with limited impact on current expenditure levels. Crucially, we find that the strength and persistence of these fiscal responses depend on the fiscal resilience of municipal governments. Specifically, local governments with both low debt service and high tax autonomy exhibit the most robust and sustained post-disaster responses. In contrast, highly indebted local governments display more modest fiscal adjustments, even when endowed with significant tax autonomy. This suggests that while tax autonomy enhances response capacity, it is most effective when coupled with sufficient fiscal space.

From a policy perspective, these findings underscore the need to strengthen the institutional and financial architecture that supports local fiscal resilience. In particular, ensuring timely, predictable and equitable access to external resources is essential for enabling municipal governments, especially those with limited fiscal space, to respond effectively and sustain recovery efforts after a disaster. At the same time, greater emphasis should be placed on building fiscal buffers in anticipation of future shocks. Accumulating reserves or stabilization funds during periods of fiscal stability can enhance local governments' capacity to absorb climate-related shocks without resorting to disruptive budget cuts or unsustainable borrowing. As extreme weather events become more frequent and severe, reinforcing these tools is critical to safeguarding the continuity of public services and long-term financial sustainability of Italian municipal governments.

The rest of the paper is organized as follows. Section 2 outlines the theoretical framework, including the municipal budget constraint and the concept of fiscal resilience. Section 3 describes the institutional setting for natural disaster management in Italy, focusing on the emergency declaration process and the governance of post-disaster response. Section 4 presents the empirical analysis, including data sources, key variables and the identification strategy. Section 5 discusses the main results, including dynamic treatment effects, budget composition and heterogeneity by fiscal resilience. Section 6 concludes with policy implications and directions for future research.

2 Theoretical framework

2.1 The budget constraint of municipal governments

The budget constraint of a municipal government formalizes how local authorities balance their fiscal instruments to ensure financial sustainability over time. For municipal government i in year t, the budget constraint can be expressed as:

$$T_{i,t} + \mathrm{Tr}_{i,t} + \Delta B_{i,t} = G_{i,t} + rB_{i,t-1}, \tag{1}$$

where the left-hand side denotes the total fiscal resources available to the municipal government. These include own-source tax revenues ($T_{i,t}$), intergovernmental transfers ($\mathrm{Tr}_{i,t}$) received from higher levels of government (regional and national) and net new borrowing ($\Delta B_{i,t}$), i.e., the change in outstanding debt. The right-hand side captures total fiscal obligations. These comprise primary expenditure ($G_{i,t}$), which includes both current and capital outlays and interest payments on existing debt ($rB_{i,t-1}$), where r

denotes the nominal interest rate and $B_{i,t-1}$ is the stock of debt carried over from the previous period.

We are interested in how exogenous natural disasters, particularly floods and landslides, affect the dynamics of the municipal government's budget constraint. The theoretical implications of such shocks can be explored by differentiating (1) with respect to an exogenous hydrogeological event:[1]

$$\frac{\partial G_{i,t}}{\partial Flood} = \underbrace{\frac{\partial T_{i,t}}{\partial Flood}}_{\text{Tax revenues}} + \underbrace{\frac{\partial \mathrm{Tr}_{i,t}}{\partial Flood}}_{\text{Transfers}} + \underbrace{\frac{\partial \Delta B_{i,t}}{\partial Flood}}_{\text{New debt}} - \underbrace{r\frac{\partial B_{i,t-1}}{\partial Flood}}_{\text{Debt service}} \tag{2}$$

Equation (2) states that the total effect of a natural disaster on municipal government's expenditure, $\frac{\partial G_{i,t}}{\partial Flood}$, depends on four key fiscal channels:

- Tax revenue often declines in the aftermath of natural disasters due to a combination of factors: disruption to local economic activity, destruction of taxable assets (e.g. buildings, businesses) and population displacement. Assuming constant tax rates, these effects erode the local tax base, reducing revenue collections. The overall fiscal impact, however, also depends on the elasticity of the tax base with respect to disaster exposure $\left(\frac{\partial T_{i,t}}{\partial Flood} \lesseqgtr 0\right)$ (Leiter et al., 2009). Theoretically, the response is ambiguous: on one hand, municipal governments may raise tax rates to compensate for shrinking bases; on the other, they might lower them to alleviate the burden on affected households and firms or to stimulate recovery. This trade-off reflects the tension between short-term revenue needs and long-term economic sustainability.

- Intergovernmental transfers typically increase following disasters, especially under an official State of Emergency, which activates targeted emergency funding from higher levels of government (Lodi et al., 2023). A positive marginal effect $\left(\frac{\partial \mathrm{Tr}_{i,t}}{\partial Flood} > 0\right)$ is expected when a declaration leads to increased transfer allocations.

- New debt issuance may increase as municipal governments turn to borrowing to finance reconstruction and resilience investments $\left(\frac{\partial \Delta B_{i,t}}{\partial Flood} \geq 0\right)$. However, the magnitude of this response depends on existing debt burden. Legal borrowing limits, market conditions and fiscal rules may constrain municipal governments' ability to take on additional debt (Noy and Nualsri, 2011).

- Debt service obligations can significantly constrain fiscal policy, particularly when municipal governments enter a disaster period with an already elevated debt burden. In such cases, a large share of the budget is pre-committed to interest payments ($rB_{i,t-1}$), reducing the fiscal space available for essential services and post-disaster interventions. If disasters require additional borrowing, the resulting increase in outstanding debt raises future debt service costs $\left(r\frac{\partial B_{i,t}}{\partial Flood}\right)$, further tightening budgetary constraints. Over time, this can erode public investment capacity, delay reconstruction and weaken fiscal resilience (Melecky and Raddatz, 2015).

[1] We assume the interest rate is exogenous and unaffected by the shock, i.e., $\frac{dr}{dFlood} = 0$. While Jerch et al. (2023) shows that disaster exposure can raise the local government's borrowing costs in the United States, where local governments rely on market-based debt issuance, in the Italian context this effect is unlikely. Borrowing by municipal governments in Italy is heavily regulated and predominantly mediated by centralized institutions such as the *Cassa Depositi e Prestiti*, which offer uniform loan conditions regardless of local shock exposure. This institutional setup insulates municipal interest rates from idiosyncratic shocks, making the assumption of exogeneity plausible.

In the aftermath of a disaster, municipal governments may face a negative feedback loop: reduced revenues and rising debt costs lead to budget cuts, which degrade public service quality and delay reconstruction, further undermining local recovery. In more favourable cases, timely and sufficient transfers may offset revenue losses, enabling local governments to sustain or even expand spending during the recovery phase.

Indeed, natural disasters often necessitate large-scale capital expenditures to repair damaged infrastructure and enhance resilience to future events. Financing such investments typically involves new borrowing, leading to an increase in the stock of outstanding debt (Chen, 2020; Deryugina, 2022; Rizzi, 2022; Welsch et al., 2022). Crucially, capital spending decisions made in the immediate aftermath of a disaster have long-term consequences, as they influence a municipality's future economic trajectory, service delivery capacity and speed of recovery (Tonetto et al., 2025). However, the ability of local governments to scale up investment in response to shocks is frequently constrained by high debt service obligations, which pre-commit a substantial share of the budget to interest payments. Municipal governments facing elevated debt service may struggle to secure additional credit, even when reconstruction needs are urgent and pressing. As a result, the timeliness and adequacy of disaster response may depend not only on the availability of external support but also on the pre-disaster fiscal position (Auh et al., 2022).

To understand how these constraints operate, we rearrange the municipal government's budget constraint in Equation (1) to make explicit the financial needs generated by a fiscal shock:

$$\Delta B_{i,t} = G_{i,t} - T_{i,t} - \mathrm{Tr}_{i,t} + rB_{i,t-1}. \tag{3}$$

This expression shows that any budget shortfall, comprising the primary deficit ($G_{i,t} - T_{i,t} - \mathrm{Tr}_{i,t}$) and interest payments on existing debt ($rB_{i,t-1}$), must be financed through new borrowing ($\Delta B_{i,t}$). In the aftermath of a disaster, expenditures typically rise ($\Delta G_{i,t} > 0$), while revenues and intergovernmental transfers may simultaneously decline ($\Delta T_{i,t} + \Delta \mathrm{Tr}_{i,t} < 0$). Under these conditions, municipal governments already facing high debt service obligations ($rB_{i,t-1} > 0$) may be unable, or unwilling, to expand borrowing further due to credit constraints or fiscal rules. This effectively reduces their fiscal space ($\Delta B_{i,t} \approx 0$), forcing a contraction in expenditure precisely when additional investment is most needed.

In sum, the capacity of a municipal government to respond fiscally to natural disasters depends on the flexibility of each component in its budget constraint. While intergovernmental transfers can play a stabilizing role, the overall ability to absorb shocks is shaped by inherited debt service burden, institutional limitations and access to credit markets. Understanding these dynamics is central to our empirical analysis.

2.2 Fiscal resilience

Natural disasters exert significant fiscal stress on local governments, as emergency spending increases precisely when local revenues decline (Noy and Edmonds, 2019). Municipal governments are at the forefront of disaster response, tasked with coordinating relief efforts, sustaining essential public services and initiating reconstruction, often under tight budgetary and institutional constraints. These simultaneous demands can jeopardize long-term financial sustainability, especially in the absence of sufficient fiscal buffers.

In this context, the concept of fiscal resilience has gained prominence as a critical dimension of local government performance under stress (Lazzaroni and van Bergeijk, 2014; Zhang and Guo, 2024). Adapted from ecological theory, fiscal resilience in public finance refers to the ability of a municipal government to withstand external shocks and restore fiscal stability without enduring persistent damage to service delivery or financial health (Ahrens and Ferry, 2020). A fiscally resilient local government is therefore able to quickly mobilize financial resources, sustain essential spending, and avoid destabilizing cuts or excessive borrowing during the recovery.

This fiscal capacity is not evenly distributed across municipal governments. Indeed, key determinants of fiscal resilience include the pre-disaster financial position, debt levels, fiscal autonomy and access to external support (Lam et al., 2017). In adverse scenarios, declining revenues combined with rigid expenditure commitments (e.g., personnel costs or debt service) can trigger a vicious cycle: budgetary contraction, delayed recovery and erosion of the local tax base. Conversely, when adequate buffers or timely transfers are in place, municipal governments can sustain, or even expand, critical spending.

Empirical research supports this framework. For instance, Chen (2020) shows that US local governments with larger unreserved fund balances and disaster reserves experience less fiscal stress following natural disasters. Similarly, Miao et al. (2023) find that wealthier counties increase expenditures and recover tax revenues more quickly, while poorer counties suffer protracted revenue losses and resort to greater borrowing. These disparities suggest that both financial health and institutional access to support networks critically influence fiscal resilience.

In the Italian context, fiscal resilience is shaped by a unique combination of legal constraints and institutional arrangements. Historically, Italian municipal finance has operated under national and European rules aimed at enforcing budget discipline. Until 2016, the Domestic Stability Pact (*Patto di Stabilità Interno*) imposed limits on local deficits.[2] The 2012 constitutional reform enshrined the principle of balanced budgets (*Pareggio di Bilancio*), allowing exceptions only in officially declared emergency situations. The current framework, introduced by L. 208/2015, grants greater spending autonomy but maintains strict controls on debt sustainability and accounting harmonization.[3]

Critically, Italian municipal governments face binding limits on borrowing: they can only incur debt to finance capital investment, not current expenditures. Interest payments must remain below 10% of current revenue (L. 190/2014) and borrowing requires compliance with regional and national fiscal targets. As a result, debt-financed recovery is only viable for municipal governments with low pre-existing debt burden. Highly indebted municipal governments may be legally unable, or politically unwilling, to assume new debt, even when facing urgent reconstruction needs (Berset et al., 2023; Jerch et al., 2023). This highlights how disaster exposure interacts with existing debt constraints to shape fiscal outcomes.

Equally important is the revenue side of the government's budget equation. A municipal government's fiscal autonomy, i.e., its ability to raise and manage revenues independently, plays a central role in

[2] See Art. 31 of L. 183/2011, as amended by Art. 1 of L. 228/2012.
[3] See also L. 232/2016 and L. 145/2018 on surplus use and accounting standards.

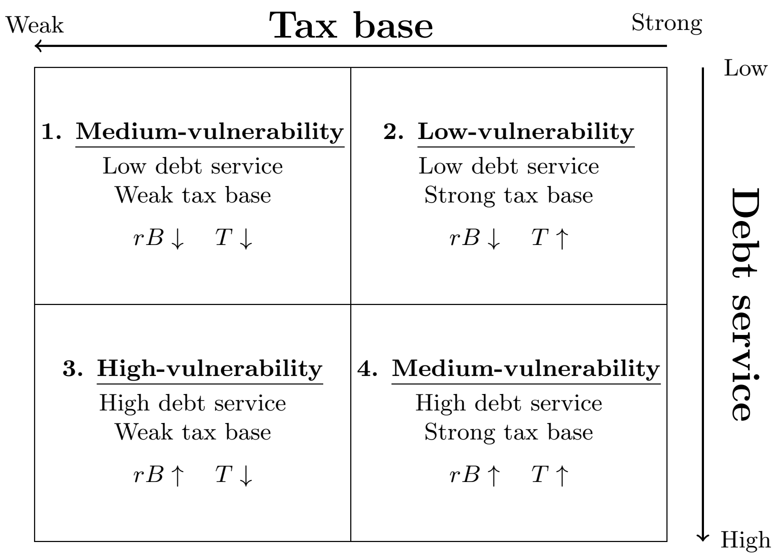
resilience. Municipalities with a strong local tax base can adjust tax rates, mobilize fees, or leverage reserves to cover emergency costs. Those reliant on intergovernmental transfers are more vulnerable to delays, uncertainty, or political discretion in fund allocation. While transfers often function as automatic stabilizers during declared emergencies, they are not always timely or sufficient to close budget gaps (Naess et al., 2005).

Empirical evidence confirms the importance of a diversified and robust revenue structure. For example, Shi and Varuzzo (2020) find that US coastal cities with broader tax bases face less fiscal risk from climate-related hazards. Moreover, strong own-source revenues enhance creditworthiness, enabling municipalities to access emergency borrowing on more favorable terms (Barbera, 2017).

In Italy, where municipal governments depend heavily on intergovernmental transfers, limited fiscal autonomy can significantly hinder timely and effective disaster response. Smaller municipalities, often characterized by narrow tax bases and legally capped tax rates, lack the flexibility to mobilize additional financial resources when emergencies arise. As a result, they are compelled to rely on regional or national support, which may be subject to administrative delays, conditionality or misalignment with local priorities. This dependence can slow recovery efforts and exacerbate fiscal stress. In contrast, municipal governments with greater fiscal autonomy are better equipped to respond swiftly and independently to emergencies, bridging immediate financing gaps while awaiting external assistance.

Bringing these elements together, we conceptualize fiscal resilience as a function of two interrelated dimensions: (i) the debt service burden, captured by the ratio of interest payments to current revenues, and (ii) the strength of the autonomous revenue base, measured by the share of own-source taxes in current revenues. Figure 1 illustrates how municipal governments are positioned along these two dimensions, identifying four distinct configurations of fiscal vulnerability.

Figure 1: Fiscal vulnerability of local governments



Note. Municipalities are classified into four categories based on their relative levels of debt service and tax autonomy. Fiscal vulnerability increases with higher debt service burden and weaker own-source revenue capacity. Authors' own elaboration.

A municipal government characterized by both low debt service obligations and strong tax autonomy

(Quadrant 2) possesses the greatest fiscal resilience. It has both the flexibility to access credit markets and a robust local revenue base, enabling it to respond to shocks with minimal reliance on external support. In contrast, municipal governments with high debt service and weak own-source revenues (Quadrant 3) are fiscally vulnerable on both dimensions, with limited capacity to borrow and constrained fiscal autonomy, significantly impairing their ability to mount an effective response to exogenous shocks.

The remaining configurations (Quadrants 1 and 4) reflect intermediate positions that entail fiscal trade-offs. A municipal government in Quadrant 1, with low debt service but limited revenue autonomy, may have short-term borrowing room but lack the fiscal capacity to service additional debt over time. Conversely, a municipal government in Quadrant 4, with strong own-source revenues but high debt service, may face legal or institutional constraints that limit further borrowing, despite its revenue-generating potential.

This two-dimensional framework is consistent with broader definitions of fiscal space as the capacity to expand public spending without jeopardizing long-term fiscal sustainability (Chapman, 2008; Gagliardi et al., 2022). It provides the conceptual basis for our empirical classification of municipal fiscal resilience.

3 Natural disaster management in Italy

Italy's civil protection system, a core component of the country's disaster risk management and multi-level resilience governance, constitutes the institutional backbone of our empirical strategy. It defines both the legal framework for public intervention in the wake of hydrogeological disasters and the fiscal instruments through which reconstruction funds are channelled to municipal governments. This section outlines the key institutional features relevant to our identification approach.[4]

The modern National Civil Protection Service (NCPS) was established by L. 225/1992, which for the first time conceptualized disaster management as a continuous cycle encompassing forecasting, prevention, emergency response and recovery. However, major disasters – including the Irpinia earthquake (1980), the Piemonte floods (1994), the L'Aquila earthquake (2009) and the Emilia earthquake (2012) – exposed persistent coordination failures. These challenges prompted significant institutional reforms, notably D.L. 59/2012 (converted into L. 100/2012), followed by the Civil Protection Code (Leg. Decree 1/2018). The Code consolidated a previously fragmented legal framework and formalized key principles of disaster governance: solidarity, subsidiarity and unified command. Most relevant for our study, it (i) standardizes the classification of emergency events, (ii) imposes a uniform limit on national States of Emergency, and (iii) centralizes the entire response chain, from emergency relief to long-term reconstruction, within the Civil Protection Service until the restoration of ordinary administrative authority (Articles 24–27).

Disaster response in Italy follows a multi-level governance structure. At the local level, mayors serve as the primary civil protection authorities. Regional presidents (NUTS-2 level) coordinate responses to medium-scale events. In cases of major disasters, the Department of Civil Protection, under the direct authority of the Prime Minister, takes command via the Permanent Operational Committee (POC) (Natoli, 2022). When local capacity is overwhelmed, the Council of Ministers, upon formal request

[4] For a discussion of the legal and institutional evolution of Italy's civil protection system, see Spuntarelli (2021) and Del Pinto et al. (2024), who examine both the normative foundations and operational implementation.

from the affected region, issues a State of Emergency decree. This decree appoints a Commissioner with extraordinary powers to issue urgent orders, including derogations from standard administrative procedures. Crucially for municipal finance, the decree also authorizes the creation of a special accounting line into which state funds are deposited and from which all emergency-related expenditures are disbursed.

Initial relief is financed through the National Emergency Fund and may be supplemented by ad hoc appropriations, intra-ministerial reallocations, or, for large-scale disasters, grants from the E.U. Solidarity Fund. Between 2016 and 2022, the Council of Ministers declared 92 hydrogeological States of Emergency, allocating approximately €991.75 million across 104 provinces and 4,045 municipalities (Table 1).[5]

Table 1: Hydrogeological States of Emergency declared in Italy, 2016–2022

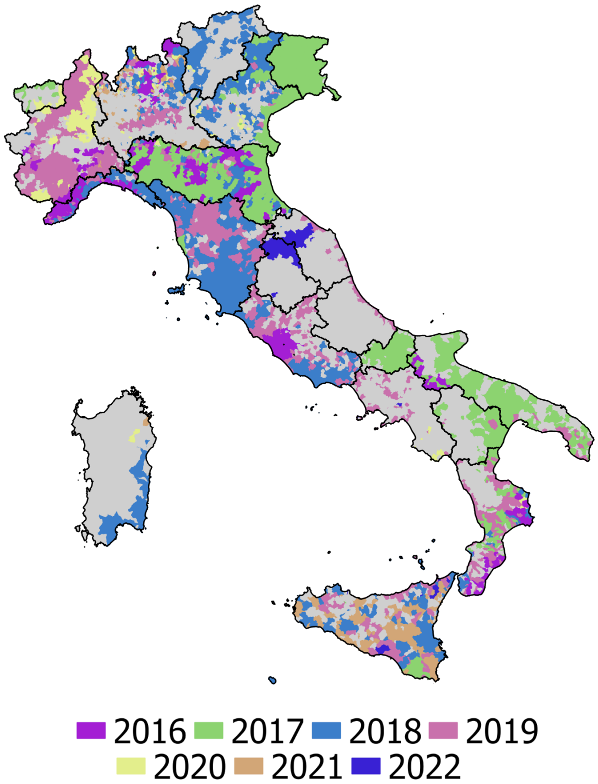
Region	**Number of emergency declarations**	**Provinces involved (NUTS-3)**	**Municipalities involved (LAU)**	**Allocated funds (million €)**
Abruzzo	1	3	19	10.94
Basilicata	5	2	31	22.37
Calabria	6	5	254	64.22
Campania	5	5	82	31.82
Emilia-Romagna	12	9	327	183.73
Friuli-Venezia Giulia	4	4	215	30.42
Lazio	3	5	194	8.38
Liguria	8	4	222	87.52
Lombardia	7	12	590	61.08
Marche	2	5	35	24.33
Molise	1	2	117	5.40
Piemonte	7	8	837	136.62
Puglia	4	6	167	41.38
Sardegna	2	3	46	7.26
Sicilia	8	9	258	52.07
Toscana	5	11	246	79.38
Trentino-Alto Adige	2	2	82	6.65
Umbria	1	1	12	0.60
Valle d'Aosta	2	1	27	5.72
Veneto	7	7	285	131.87
Italy	**92**	**104**	**4,045**	**991.75**

Note. Figures refer to hydrogeological States of Emergency formally declared by the Council of Ministers between 2016 and 2022. The number of affected provinces and municipalities reflects unique jurisdictions involved across all declarations; areas impacted by multiple events are counted only once. Allocated funds represent the total financial resources disbursed under each State of Emergency decree, divided equally among the regions affected by that event, and then aggregated at the regional level.

Because States of Emergency are event-specific, their geographic coverage varies across time and space. Some municipalities are affected multiple times, while others remain untouched. This staggered and heterogeneous exposure structure, illustrated in Figure 2, forms the empirical foundation of our identification strategy. Two institutional features make treatment assignment plausibly exogenous to pre-existing municipal fiscal conditions. First, eligibility is rule-based: municipalities are automatically included if they fall within the declared emergency perimeter, and the list is not subject to post-declaration lobbying. Second, post-disaster expenditures are financed almost entirely through central government transfers (OECD, 2018; Spuntarelli, 2021). These features mitigate concerns about selection bias and simultaneity, supporting a quasi-experimental interpretation of the observed fiscal responses.

[5] Some municipalities were affected repeatedly. Forlì-Cesena experienced 12 events; Bologna, Ferrara, Modena, Parma, and Reggio Emilia each faced 11; Piacenza and Ravenna were hit 10 times. Several municipalities, including Argenta, Cesenatico, Comacchio, Compiano, Farini, Modena, and Neviano degli Arduini, were affected by up to nine events. However, most municipalities (2,309) were affected only once.

Figure 2: First year of treatment across municipalities



Note. The map displays the year in which each municipality was first affected by a hydrogeological State of Emergency declared between 2016 and 2022. Colors represent the year of initial exposure, while grey indicates municipalities that were not affected during the observation period. Authors' own elaboration based on administrative records.

Taken together, these institutional arrangements provide a strong basis for causal identification. The State of Emergency mechanism, governed by standardized legal procedures and objective eligibility rules, generates plausibly exogenous variation in the timing and geographic scope of treatment. Moreover, the centralization of emergency funding, primarily via intergovernmental capital transfers, reduces the influence of local fiscal discretion on treatment intensity. As a result, Italy's civil protection architecture creates a structured, rule-based and resource-endowed setting for disaster response that closely approximates a natural experiment. Leveraging this context, we use variation in the timing and location of State of Emergency declarations to estimate the fiscal effects of hydrogeological disasters.

4 Empirical analysis

4.1 Data

To estimate the fiscal effects of hydrogeological disasters on municipal budgets, we construct a comprehensive longitudinal dataset covering the universe of Italian municipalities from 2016 to 2022. This dataset merges administrative, fiscal, and institutional sources, enabling us to capture the timing, intensity and fiscal consequences of disaster exposure at high spatial and temporal resolution.

Municipalities are classified as treated if they meet two conditions: (i) they are included in a formal State of Emergency declaration issued by the national government, and (ii) they receive post-disaster reconstruction funds through a dedicated special accounting line. These criteria ensure that treatment reflects both legal recognition of the event and the actual fiscal transfer of resources. Between 2016 and 2022, a total of 4,045 municipalities were affected by at least one hydrogeological State of Emergency, across 16 major multi-municipality events (see Tables A.1-A.2). Our primary source for disaster exposure is the georeferenced database by Gatto et al. (2023), which documents all floods and landslides associated with formal emergency declarations, standardizing definitions and administrative classifications.

To strengthen identification, we exclude from the control group any municipality that was affected by a hydrogeological State of Emergency between 2013 and 2016. This pre-sample buffer reduces the risk of latent treatment exposure or fiscal adjustments in anticipation of future shocks, thereby enhancing the credibility of our counterfactual.

Table 2 summarizes the cumulative number of municipalities treated for the first time in each year from 2017 to 2022, along with their shares of national population, public expenditure and revenue. We focus exclusively on first-time treatment episodes, excluding municipalities that experienced multiple declarations during the study period. This restriction improves comparability and identification by avoiding confounding effects from overlapping shocks, which occur irregularly and vary in fiscal impact.[6]

Table 2: Cumulative exposure to first-time State of Emergency: treated municipalities, population and budget shares (2017–2022)

	Treated municipalities	**Population share**	**Expenditure share**	**Revenue share**
2017	263	0.064	0.053	0.053
2018	470	0.123	0.107	0.108
2019	1,077	0.308	0.342	0.346
2020	1,296	0.363	0.435	0.443
2021	1,444	0.401	0.457	0.463
2022	1,476	0.408	0.439	0.440

Note. The table reports the cumulative number of municipalities treated for the first time between 2017 and 2022, along with their shares of national population, expenditure and revenue. Municipalities that received State of Emergency declarations prior to 2017 or experienced multiple treatments are excluded from the count. Shares are calculated relative to the full universe of municipalities observed in each year.

We analyze treatment effects on a range of budgetary outcomes using data from OpenBDAP, the official accounting database maintained by the Italian Treasury (*Ragioneria Generale dello Stato*). On the expenditure side, our primary variable is total expenditure, which includes all authorized budgetary outlays in a given fiscal year. We further disaggregate total expenditure into:

- Current expenditure, which includes salaries, utilities, materials and other costs essential for the routine provision of services such as education, social assistance and local administration.
- Capital expenditure, which captures investments in infrastructure and durable assets, such as roads, water systems and public buildings, critical for long-term development and post-disaster recovery.

[6] Repeated treatments pose significant challenges in staggered adoption settings. Municipalities are often exposed to disasters at different times and in overlapping sequences, making it difficult for standard difference-in-differences estimators to accommodate short intervals between events and heterogeneous dynamic effects. Additionally, the number of municipalities sharing identical timing and patterns of multiple exposures is typically too small to support credible subgroup analyses. As noted by De Chaisemartin and d'Haultfoeuille (2020) and Goodman-Bacon (2021), these complexities can undermine key assumptions such as parallel trends and stable treatment assignment. Focusing on first exposures improves both transparency and internal validity, while still capturing the bulk of disaster-related fiscal impacts.

We also examine expenditure composition by functional "missions" (*Missioni*), which classify spending according to policy areas (e.g., civil protection and environmental protection). These disaggregations allow us to investigate whether disaster exposure leads to targeted reallocations across municipal functions.

On the revenue side, we examine total revenues and their breakdown by institutional "titles" (*Titoli*). Titles categorize revenues according to their institutional source, such as local taxes, intergovernmental transfers, or asset sales, providing a structured view of the composition of municipal income. This classification system, standardized across all Italian municipal governments, facilitates consistent comparisons over time and across jurisdictions. Full details are reported in Table A.3.

In line with our theoretical framework, we investigate whether the fiscal impact of disaster exposure depends on municipal fiscal resilience. We construct an empirical typology based on two indicators:

- Debt burden, high if the share of interest payments in current revenue exceeds the 2016 median.
- Tax autonomy, high if the share of tax revenues in current revenue exceeds the 2016 median.

Combining these binary indicators yields four fiscal resilience profiles: (i) vulnerable (high debt burden and low tax autonomy), (ii) resilient (low debt burden and high tax autonomy), and (iii) two intermediate types. Table 3 reports the distribution of treated municipalities across these profiles.

Table 3: Distribution of treated municipalities by fiscal resilience profiles (2016–2022)

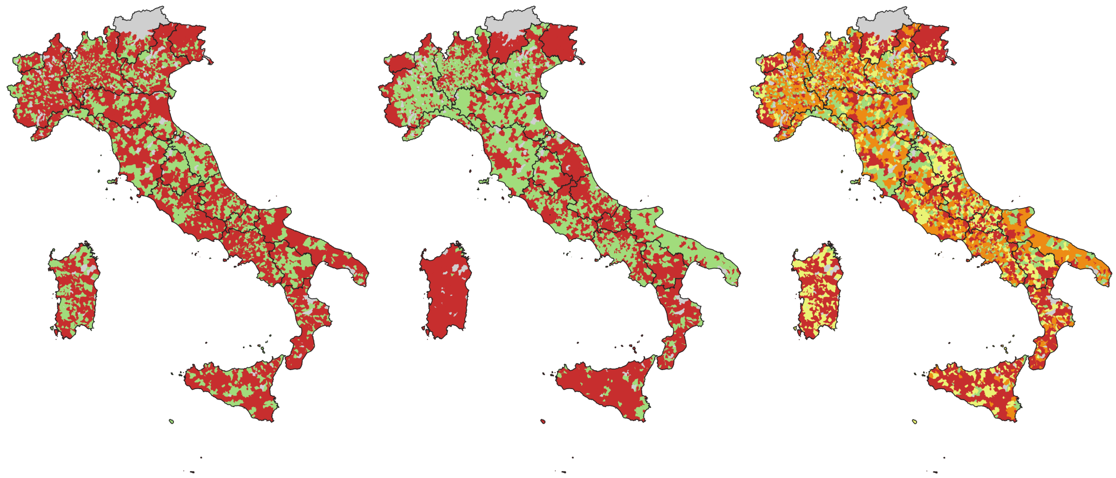
	Tax autonomy		
Debt service	**Weak**	**Strong**	**Total**
Low	222	222	444
High	497	535	1,032
Total	719	757	1,476

Note. The table reports the number of municipalities affected by at least one hydrogeological disaster (2016–2022), classified by fiscal resilience. Debt burden is defined as "high" if the average ratio of interest payments to current revenues exceeds the 2016 sample median. Tax autonomy is defined as "high" if the share of tax revenues to current revenues exceeds the 2016 sample median. Municipalities are grouped into four fiscal resilience categories based on these binary indicators.

A relatively small share of treated municipalities (15%) are classified as fiscally resilient, whereas approximately one-third exhibit high fiscal vulnerability. This heterogeneity reinforces the need to assess how initial fiscal capacity conditions the response to disaster shocks.

Figure 3 illustrates the geographical distribution of fiscal resilience across Italian municipalities. Panel (a) presents debt burden; Panel (b) shows tax autonomy; and Panel (c) combines both dimensions into a four-category resilience typology. The maps reveal substantial territorial heterogeneity in fiscal conditions: municipal governments with high debt burden or low tax autonomy are not confined to a specific area but are dispersed across all macro-regions, including the North, Center and South. The composite typology in Panel (c) highlights clusters of fiscal vulnerability in traditionally disadvantaged southern areas as well as in structurally weaker inland and mountainous zones of the Center-North. These patterns emphasize the importance of accounting for both geographic and structural disparities when assessing local governments' capacity to absorb and respond to disaster shocks.

Figure 3: Geographic distribution of municipal fiscal indicators



(a) Debt service (b) Tax autonomy (c) Fiscal resilience

Note. This figure displays the spatial distribution of fiscal characteristics across Italian municipalities. Panel (a) maps debt service, measured as the ratio of interest payments to current revenues, distinguishing above- and below-median values. Panel (b) shows tax autonomy, defined as the share of tax revenues in current revenues. Panel (c) combines these two indicators into a four-category typology of fiscal resilience: resilient (low debt service, high autonomy), vulnerable (high debt service, low autonomy), and two intermediate profiles.

This fiscal typology is central to our empirical strategy. It enables us to test whether municipal governments with stronger fiscal fundamentals, i.e., lower debt burden and greater tax autonomy, are better positioned to sustain or expand expenditure following a disaster. In line with the theoretical framework outlined in Section 2, we hypothesize that resilient municipal governments are more likely to invest in reconstruction and climate adaptation, whereas those with constrained fiscal space may be forced to retrench or rely on external transfers, slowing recovery and reducing autonomy. Identifying these heterogeneous responses is critical for informing the design of equitable and effective disaster funding mechanisms.

To empirically assess these differential effects, we integrate treatment and budget data with a rich set of covariates capturing socio-economic, geographic and institutional characteristics at the municipal level. These include: (i) demographic and territorial indicators; (ii) household income levels; (iii) a composite disaster vulnerability and resilience index; and (iv) an institutional quality index. Table 4 summarizes the key variables used in the analysis along with their respective data sources.

Table 4: Overview of key variables and data sources

Variable	**Years**	**Source**
Municipal budget data	2016–2022	Ragioneria Generale dello Stato
Demographics	2016–2022	ISTAT
Geography	2016–2022	ISTAT
Household income	2016–2022	MEF
Disaster resilience/vulnerability	2013–2022	Marin et al. (2021)
Disaster exposure	2013–2022	Gatto et al. (2023)
Institutional quality	2001–2022	Cerqua et al. (2025)

Note. This table lists the principal variables used in the empirical analysis, along with their temporal coverage and data sources. Variables encompass financial, demographic, geographic, institutional and disaster-related dimensions at the municipal level.

4.2 Descriptive statistics

Table 5 presents summary statistics for municipal revenues and expenditures in Italy over the 2016–2022 period, highlighting substantial heterogeneity in both budget size and composition across municipal governments.

On the revenue side, the largest and most stable component is current revenues, which encompass locally raised taxes such as the municipal property tax, waste collection and disposal fees and local income taxes. These revenues average €3.62 million per municipal government annually, accounting for nearly 38% of total revenue and reflect autonomous fiscal capacity of local governments. The large standard deviation (€20.1 million) indicates significant disparities driven by differences in population size, economic structure and local tax policy. Capital revenues are the second-largest category, contributing 18.1% of total income. These include asset sales, investment-related transfers and one-off flows such as compensation or co-financing for infrastructure. Their importance typically increases in post-disaster periods, when rebuilding efforts and co-financing needs intensify. Current transfers, which represent 13.9% of revenues, originate from regional, national or EU sources. These intergovernmental transfers serve redistributive and compensatory functions and often rise in response to disaster shocks. Revenues for third parties make up 13.4% of total revenues and are highly volatile (standard deviation: €31.6 million). These include pension contributions and reimbursements for delegated services. While not part of the discretionary budget, their size reflects administrative scale, particularly in larger municipalities. Extra-tax revenues, such as fines, service fees and rental income, account for 11.7% of revenues, averaging €1.12 million annually. Though secondary in scale, they provide valuable fiscal flexibility, particularly in tourist areas or asset-rich jurisdictions. In contrast, cash advances, borrowing and sales of financial assets contribute only marginally to the budget (each $< 1\%$ of revenues). Due to their limited fiscal relevance and irregular use, these categories are thus excluded from the main empirical analysis.

On the expenditure side, the largest category is institutional and general public services, accounting for 26% of total spending. This mission captures core governance and administrative functions, forming a stable component across all municipal governments. Third-party services are the second-largest category (14.2%), mirroring Title 9 on the revenue side. It reflects the role of municipal governments as intermediaries in delegated services, such as payroll and pension disbursement, with a greater role in larger or more complex administrations. The mission sustainable development and land management ranks third, absorbing 14% of expenditures. This includes spending on environmental protection, urban planning, and conservation, areas of heightened relevance in disaster-prone regions. Transportation and mobility and social and family policies follow, representing 9.2% and 8.0% of expenditures, respectively. These cover local infrastructure and essential social services, relevant across a wide range of municipal governments. Education comprises 7.4% of expenditures, largely reflecting the municipal responsibility for maintaining primary school facilities and related services. Several smaller but consistently reported missions also merit attention, including public order (2.4%), cultural heritage (3.7% combined) and spatial planning (3.7%). In contrast, several missions, including justice, international relations and agriculture and fisheries, are largely inactive, with more than 80% zero observations. To ensure comparability and mitigate censoring bias, the empirical analysis focuses on missions with non-missing data in at least 60% of municipal-year observations.

A complete overview of descriptive statistics, including mean values, standard deviations, average shares and zero-observation rates, is provided in Table 5.

Table 5: Descriptive statistics of municipal revenue and expenditure categories (2016–2022)

Revenue categories (Titles)						
Item	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Avg. Share**	**% of Zero**
T1. Current revenue	3.62	20.10	0.00	934.00	37.75%	2%
T2. Current transfers	1.26	7.68	0.00	644.00	13.89%	2%
T3. Extra-tax revenue	1.12	6.70	0.00	349.00	11.73%	2%
T4. Capital revenue	1.35	6.61	0.00	662.00	18.10%	2%
T5. Sale of financial assets	0.05	0.79	0.00	57.00	0.26%	93%
T6. Borrowing	0.17	4.25	0.00	523.00	0.98%	80%
T7. Cash advances	0.78	14.40	0.00	1 310.00	3.84%	81%
T9. Revenue on behalf of third parties	2.03	31.60	0.00	2 820.00	13.44%	2%
Total revenue	10.40	77.50	0.00	5 470.00	100%	2%
Expenditure categories (Missions)						
Item	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Avg. Share**	**% Zero**
M1. Institutional and general services	1.77	7.97	0.00	483.00	25.98%	2%
M2. Justice	0.00	0.15	0.00	26.00	0.02%	92%
M3. Public order and security	0.27	1.97	0.00	102.00	2.42%	10%
M4. Education	0.59	2.61	0.00	156.00	7.36%	3%
M5. Protection of cultural heritage	0.17	0.94	0.00	59.10	1.78%	12%
M6. Youth, sport and leisure	0.15	0.69	0.00	33.80	1.89%	11%
M7. Tourism	0.06	0.27	0.00	18.70	0.75%	47%
M8. Spatial planning and housing	0.27	1.07	0.00	47.30	3.74%	15%
M9. Sustainable development	1.33	6.14	0.00	322.00	14.05%	2%
M10. Transportation and mobility	0.69	5.77	0.00	367.00	9.22%	7%
M11. Civil relief	0.07	0.61	0.00	30.10	0.94%	33%
M12. Social policies and family	0.86	4.44	0.00	239.00	8.01%	3%
M13. Health protection	0.01	0.04	0.00	1.57	0.09%	77%
M14. Economic development	0.07	0.60	0.00	38.30	0.66%	39%
M15. Employment and training	0.01	0.10	0.00	10.90	0.08%	82%
M16. Agriculture and fisheries	0.01	0.07	0.00	6.40	0.13%	79%
M17. Energy	0.05	0.44	0.00	25.90	0.74%	76%
M18. Inter-municipal relations	0.01	0.09	0.00	2.80	0.20%	94%
M19. International relations	0.00	0.04	0.00	3.99	0.00%	99%
M20. Funds and provisions	0.00	0.02	0.00	1.88	0.02%	98%
M50. Public debt	0.36	4.35	0.00	337.00	3.66%	6%
M60. Financial advances	0.79	14.40	0.00	1 310.00	4.05%	81%
M99. Third-party services	2.03	31.60	0.00	2 820.00	14.20%	2%
Total expenditure	9.56	69.90	0.00	4 520.00	100%	2%

Note. All monetary values are expressed in millions of euros. “Avg. Share” indicates the average percentage contribution of each item to total revenue or expenditure. “% Zero” refers to the proportion of municipal-year observations with zero reported values for a given category. Budget items with more than 40% zero entries are excluded from the analysis due to limited coverage and lack of comparability.

Table 6 compares pre-treatment characteristics of municipalities that experienced at least one hydrogeological disaster (flood or landslide) between 2017 and 2022 (treated) with those that were never exposed to such events during the extended 2013–2022 period (never treated). The comparison includes a broad set of covariates, covering socio-demographic attributes, geographic positioning, environmental risks, and fiscal indicators, and provides a preliminary assessment of baseline differences that may influence both selection into treatment and heterogeneity in fiscal outcomes.

Treated municipalities are significantly larger, with an average population of roughly 7,160 compared to 5,630 among never-treated municipalities. At the same time, they are less densely populated (272 vs. 418 inhabitants per km^2), consistent with the geography of flood-prone areas often located in semirural or peri-urban zones. Treated municipalities are also more frequently located along the coast, with significant differences in both coastal proximity indicators.

In socio-economic terms, treated municipalities report a modestly higher average taxable income (€17,666 vs. €17,402), pointing to a slightly stronger economic base. They also show slightly lower administrative quality, though the difference is not statistically significant.

Environmental indicators confirm that treated municipalities face greater exposure to flood hazards and lower exposure to landslide risks, in line with Italy's topographic risk profile. Treated municipalities also exhibit slightly higher resilience scores and lower vulnerability levels, suggesting potentially better adaptive capacity or more robust baseline infrastructure and institutions.

Fiscal differences, though smaller in magnitude, are statistically meaningful: treated municipal governments devote a greater share of spending to public debt service and rely more heavily on current tax revenues (63.0% vs. 60.6%). These fiscal differences could shape the ex-post capacity of municipal governments to respond to disasters and underscore the relevance of accounting for baseline heterogeneity in the empirical analysis.

Overall, the observed pre-treatment differences between treated and untreated municipalities justify the use of covariate-adjusted estimators to mitigate potential bias. Full sample descriptive statistics are reported in Appendix Table A.4.

Table 6: Pre-treatment characteristics of treated and never-treated municipalities

Variable	**Never treated (a)**	**Treated (b)**	**Diff. (a–b)**	**S.E.**	**P-value (diff $\neq$ 0)**
Population	5,633	7,161	-1,528.26	743.24	0.040
Mean taxable income (€/capita)	17,402	17,666	-264.07	128.21	0.040
Municipal admin. quality (index)	103.77	103.55	0.22	0.12	0.057
Population density (inh./km^2)	418.28	272.03	146.25	26.16	0.000
Near the coast (lit) (0/1)	0.053	0.094	-0.041	0.008	0.000
Coastal (cost) (0/1)	0.125	0.164	-0.039	0.011	0.001
Urban classification (1–3)	2.586	2.603	-0.018	0.018	0.337
Resilience index (0/1)	0.535	0.548	-0.012	0.005	0.007
Vulnerability index (0/1)	0.484	0.464	0.020	0.004	0.000
Flood hazard index (0/1)	0.043	0.056	-0.013	0.003	0.000
Landslide hazard index (0/1)	0.101	0.076	0.025	0.005	0.000
Public debt expenditure / curr. rev.	0.018	0.021	-0.003	0.001	0.001
Current tax revenue / curr. rev.	0.606	0.630	-0.024	0.006	0.000

Note. The table reports mean values for a range of socio-economic, geographical, environmental and fiscal variables, comparing municipalities that experienced at least one flood or landslide between 2017 and 2022 (treated) with those that remained unexposed to such events over the period 2013–2022 (never treated). The final three columns present the difference in means (a–b), corresponding standard errors and associated p-values. All statistics refer to the unmatched sample and are measured in the pre-treatment period (2016). These covariates are used to adjust for observable differences in the estimation of treatment effects using the covariate-adjusted estimator proposed by Callaway and Sant'Anna (2021).

4.3 Empirical model

While the timing of floods and landslides is largely exogenous and unpredictable, their spatial distribution is far from random. A growing body of literature documents how disaster exposure correlates with structural characteristics such as geography, urban development, hazard history and administrative capacity (Deryugina, 2017; Kocornik-Mina et al., 2020). Municipalities near rivers or coasts, those with mountainous terrain, or those burdened by aging infrastructure are systematically more vulnerable to hydrogeological risk. Furthermore, the declaration of a State of Emergency, which governs access to public funding, is often shaped by institutional and political factors, including administrative quality and lobbying capacity (Neumayer et al., 2014).

These features pose several identification challenges. First, treatment, defined as exposure to a flood or landslide followed by official emergency recognition, is staggered across municipalities and time. Some are treated early, others later, while many remain untreated throughout the sample period. Second, municipalities differ substantially in observable characteristics such as population size, fiscal capacity and governance quality, which may jointly influence both disaster exposure and fiscal outcomes.

Standard two-way fixed effects models yield biased estimates in settings with staggered treatment timing and heterogeneous treatment effects (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). In response to these limitations, recent methodological advances propose alternative estimators that are better suited to such contexts (Roth et al., 2023). To address these concerns, we implement the estimator developed by Callaway and Sant'Anna (2021), which explicitly accounts for treatment effect heterogeneity and staggered adoption. This approach estimates group-time average treatment effects ($ATT_{g,t}$) by comparing units first treated in year g with an appropriate control group consisting of municipalities that are either not-yet treated or never treated.

To enhance comparability between treated and control municipalities, we adopt the doubly robust inverse probability weighted difference-in-differences estimator as our baseline specification. This approach relaxes strong parametric assumptions and helps mitigate bias from observable confounders, including hazard exposure, demographic characteristics and fiscal conditions, by combining outcome regression with inverse probability weighting (Sant'Anna and Zhao, 2020).

Municipalities are grouped into treatment cohorts according to their year of first exposure (g), and treatment effects are estimated by comparing outcomes in year t for each treated cohort to those of municipalities that are not yet treated or never treated. Covariates used for adjustment in the outcome and propensity score models include: the log of population and taxable income; population density and total surface area; the MAQI Index (Cerqua et al., 2025); geographic indicators for urban, coastal and near-coastal status; indices of fiscal resilience and vulnerability (Marin et al., 2021); and binary indicators for flood and landslide hazard exposure.[7]

To assess the robustness of our results, we also estimate alternative specifications using the improved doubly robust estimator, outcome regression, and inverse probability weighting methods.

The group-time average treatment effect on the treated (ATT) is defined as:

$$ATT_{g,t} = [Y(g)_t - Y(NT)_t] - [Y(g)_{g-1} - Y(NT)_{g-1}] \tag{4}$$

where $Y(g)_t$ denotes the average outcome at time t for municipalities first treated in year g, and $Y(NT)_t$ denotes the average outcome for the control group. The comparison is anchored on the common pre-treatment period $g-1$ to ensure temporal consistency.

[7] Table B.1 reports results from a balancing exercise using propensity score matching to assess the comparability between municipalities treated during 2017–2022 and those never treated between 2013–2022. The results show good balance across key covariates, with only minor residual differences in resilience and vulnerability indices. This supports the credibility of the control group used in the doubly robust inverse probability weighted diff.-in-diff. estimation.

In our baseline specification, we define the control group as the not-yet-treated. This choice enhances the plausibility of the parallel trends assumption by ensuring that treated and control units share similar potential outcomes trajectories prior to treatment. Formally, we assume:

$$\mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid X, G = g] = \mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid X, D_s = 0, G \neq g] \tag{5}$$

for all $t \geq g$ and $s \geq t$, where $D_s = 0$ indicates untreated status in period s, G is the treatment cohort and X denotes a set of observed covariates. This conditional version of the parallel trends assumption ensures that, after controlling for X, control municipalities provide valid counterfactuals for the treated.

Finally, to summarize the overall treatment effect across cohorts and post-treatment periods, we compute the Aggregated Group-Time Treatment Effect (AGTT) as a weighted average of the $ATT_{g,t}$:

$$AGTT = \frac{\sum W_{g,t} \cdot ATT_{g,t}}{\sum W_{g,t}} \tag{6}$$

where the weights $W_{g,t}$ reflect both the relative size of each treatment cohort and the precision of the corresponding ATT estimates. This aggregation provides a single interpretable estimate of the average treatment effect across treated municipalities and post-treatment periods.

The AGTT estimates form the basis of our empirical analysis in the next section, where we examine the dynamic fiscal response to hydrogeological disasters across key budget categories. We begin by presenting the baseline results and then assess heterogeneity across municipalities and budget components.

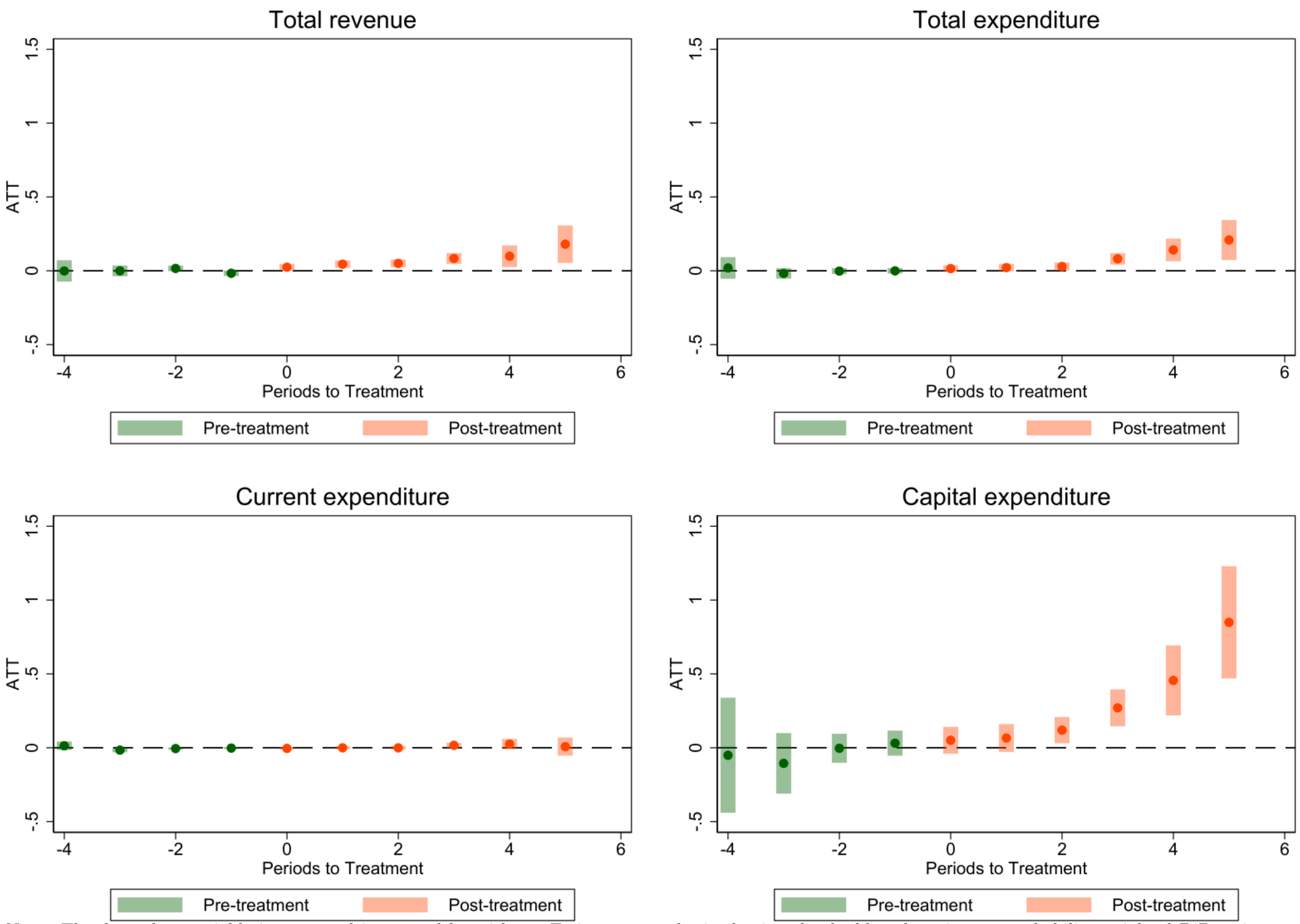
5 Results

This section presents the empirical findings of our analysis, structured around the main research questions outlined in the introduction. First, we evaluate the overall impact of hydrogeological events on municipal governments' revenue and expenditure (Section 5.1). Second, we examine how these shocks affect the composition of municipal budgets, focusing on changes across major policy areas and detailed budget classifications (Section 5.2). Third, we investigate how fiscal responses differ according to pre-disaster fiscal resilience of municipal governments, emphasizing the role of financial capacity in shaping local adaptation strategies (Section 5.3). Finally, we assess the robustness of our findings through a series of sensitivity checks, including jackknife exclusions, placebo tests and variation in exposure intensity (Section 5.4).

5.1 Revenue and expenditure

Figure 4 displays the dynamic effects of hydrogeological disasters on municipal budgets. All budget variables are expressed in natural log, so the estimated coefficients can be interpreted as semi-elasticities, i.e., percentage changes in the outcome associated with a unit change in treatment.

Figure 4: Dynamic effects of disaster exposure on total revenue and expenditure (current and capital components)



Note. The dependent variable is expressed in natural logarithms. Estimates are obtained using the doubly robust inverse probability weighted DiD estimator (Callaway and Sant'Anna, 2021), applied to the sample with not-yet-treated municipalities. Ninety-five percent confidence intervals are displayed.

Municipal revenues respond swiftly and persistently to hydrogeological shocks. The ATT on the treated is 0.049 (p<0.01), indicating a 4.9% increase relative to the pre-disaster average of €9.66 million, equivalent to approximately €0.47 million in additional resources. Dynamic estimates reveal a steadily intensifying effect: a modest 1.5% increase in the disaster year ($t + 0$), followed by 2.2% in the first post-event year, 2.9% in the second, 8.1% in the third, 14.1% in the fourth, and a peak gain of 20.9% ($\approx$ €2.02 million) five years after the event. This pattern is consistent with the gradual inflow of emergency grants and reconstruction transfers (Deryugina, 2017; Bakkensen and Barrage, 2025).

Municipal spending also rises in the wake of disasters, at a slightly faster pace than revenues. The estimated ATT is 0.058 ($p < 0.01$), corresponding to a 5.8% increase over the pre-disaster mean of €9.83 million, roughly €0.57 million in additional outlays. Expenditure rises by 2.4% in the disaster year and by 4.5% in $t + 1$, continuing its upward trajectory to reach 18.0% ($\approx$ €1.77 million) by $t + 5$. The lagged and cumulative build-up in spending aligns with the progressive roll-out of reconstruction plans, which tend to disburse funds more slowly than revenue measures take effect.

The composition of municipal spending shifts markedly in response to disasters. Current expenditure remains largely unaffected, with an ATT of only 0.004 ($p = 0.56$), reflecting a negligible 0.4% increase over the pre-disaster average of €1.12 million ($\approx$ €5,000). None of the post-treatment coefficients are both statistically significant and economically meaningful, underscoring the rigidity of personnel costs and day-to-day operational budgets (Cavallo et al., 2013).

Capital expenditure, by contrast, responds strongly and persistently. The ATT of 0.173 ($p < 0.01$) indicates a 17.3% rise compared to the pre-event mean of €4.78 million, about €0.83 million in new investments. Effects accumulate over time: 11.9% in t+2, 27.0% in t+3, 45.6% in t+4, and a substantial 84.9% increase ($\approx$ €4.06 million) by t+5. These dynamics highlight the centrality of infrastructure repair and preventive investment in post-disaster recovery strategies (Noy, 2009; Fomby et al., 2013).

Joint tests on the pre-treatment coefficients ($t-4$ to $t-1$) reveal no statistically significant differences between treated and control municipalities across all four fiscal outcomes. This supports the validity of the parallel trends assumption and lends credibility to the estimated dynamic treatment effects.

Hydrogeological disasters elicit a robust and sustained fiscal response. Revenues increase rapidly, creating fiscal space that is subsequently filled by a surge in expenditure, especially in capital investment. Current expenditure remains essentially flat, reflecting institutional inflexibility. These findings underscore the importance of timely intergovernmental transfers and investment-oriented recovery programs as key instruments for enhancing local fiscal resilience.

5.2 Breakdown by titles and missions

We now turn to the composition of municipal budgets, examining which revenue titles and expenditure missions are most affected by hydrogeological shocks. Unlike the analysis in Section 5.1, where outcomes were measured in logarithmic levels, the dependent variables here are expressed as shares of total revenue and expenditure, respectively. Accordingly, the coefficients reported in Tables 7–9 capture changes in percentage points, reflecting compositional rather than absolute shifts in the budget structure.

Table 7 provides clear evidence of a substantial reallocation toward capital revenue.

Table 7: Breakdown of revenues by Title

	Current revenue	Current transfers	Extra-tax revenue	Capital revenue	Third-party revenue
ATT (t-4)	0.0029	-0.0001	-0.0012	0.0022	-0.0159
	(0.0122)	(0.0081)	(0.0082)	(0.0186)	(0.0139)
ATT (t-3)	0.0031	-0.0022	-0.0049	0.0008	0.0006
	(0.0073)	(0.0042)	(0.0039)	(0.0106)	(0.0057)
ATT (t-2)	-0.0047	-0.0011	-0.0011	0.0073	-0.0019
	(0.0035)	(0.0020)	(0.0020)	(0.0051)	(0.0032)
ATT (t-1)	0.0065**	-0.0014	0.0003	-0.0033	0.0006
	(0.0033)	(0.0020)	(0.0017)	(0.0049)	(0.0030)
ATT (t)	-0.0072**	-0.0042*	-0.0032*	0.0155**	0.0024
	(0.0035)	(0.0022)	(0.0018)	(0.0055)	(0.0031)
ATT (t+1)	-0.0126***	-0.0018	-0.0021	0.0164**	0.0053
	(0.0038)	(0.0026)	(0.0021)	(0.0059)	(0.0040)
ATT (t+2)	-0.0124**	-0.0076***	-0.0014	0.0309***	0.0046
	(0.0045)	(0.0029)	(0.0023)	(0.0063)	(0.0040)
ATT (t+3)	-0.0163**	-0.0030	-0.0057**	0.0393***	0.0053
	(0.0059)	(0.0043)	(0.0027)	(0.0085)	(0.0057)
ATT (t+4)	-0.0257**	-0.0247***	-0.0117**	0.0604***	0.0168
	(0.0119)	(0.0078)	(0.0052)	(0.0164)	(0.0120)
ATT (t+5)	-0.0327*	-0.0430***	-0.0293***	0.1171***	0.0069
	(0.0191)	(0.0139)	(0.0087)	(0.0277)	(0.0192)
ATT (average)	-0.0138***	-0.0073**	-0.0048**	0.0310***	0.0053
	(0.0042)	(0.0029)	(0.0020)	(0.0059)	(0.0041)
Test on pre-trend (Chi sq.)	28.3960	10.5758	7.6938	22.8318	12.1117
p-value	0.0016	0.3915	0.6587	0.0114	0.2777
Unweighted average	0.3775	0.1389	0.1173	0.1810	0.1344
Weighted average	0.3496	0.1211	0.1075	0.1298	0.1954
N. of observations	27,164	27,164	27,164	27,163	27,164

Note. The dependent variable is expressed as a share of total revenue. Estimates are obtained using the doubly robust difference-in-differences estimator, combining stabilized inverse probability weighting with OLS, applied to the sample of not-yet-treated municipalities. Standard errors are reported in parentheses. Statistical significance is indicated as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

On average, the share of capital revenue increases by 3.1 percentage points following a disaster, with the effect rising steadily from 1.6 p.p. in the disaster year to over 11 p.p. five years later. These inflows predominantly consist of transfers from higher levels of government earmarked for reconstruction and preventive investment, consistent with international evidence on post-disaster fiscal responses (Garrett and Sobel, 2003; Kousky, 2014a,b; Jerch et al., 2023; Capuno et al., 2024).

This expansion is mirrored by a contraction in the relative importance of current resources: the combined share of own current revenues, current transfers and extra-tax revenues declines by approximately 2.6 p.p. on average. Notably, this is a relative decline occurring in the context of increasing total revenues (Section 5.1), and should therefore be interpreted as a shift in the composition of revenue sources rather than a reduction in their absolute levels. Third-party revenues, including funds from co-financing arrangements, public-private partnerships and E.U. transfers, show a mild upward trend but remain statistically indistinguishable from zero in most years. This suggests that the primary fiscal lifeline after disasters is intergovernmental, rather than leveraged through private or supranational actors.

A similar shift emerges on the expenditure side (Tables 8 and 9).

Table 8: Breakdown of expenditure by Mission (part I)

	General services	Public order	Education	Cultural heritage	Youth and sport	Tourism	Spatial planning
ATT (t-4)	-0.0002	0.0013	0.0104**	0.0011	-0.0016	-0.0042	0.0056
	(0.0097)	(0.0017)	(0.0049)	(0.0027)	(0.0075)	(0.0032)	(0.0053)
ATT (t-3)	-0.0028	0.0020**	-0.0021	-0.0051**	-0.0042	0.0041	0.0005
	(0.0058)	(0.0009)	(0.0035)	(0.0026)	(0.0034)	(0.0027)	(0.0031)
ATT (t-2)	-0.0024	-0.0002	0.0036	-0.0004	-0.0025**	-0.0022	0.0014
	(0.0030)	(0.0006)	(0.0025)	(0.0012)	(0.0013)	(0.0014)	(0.0022)
ATT (t-1)	0.0031	-0.0009*	-0.0033	0.0002	0.0013	0.0009	0.0000
	(0.0027)	(0.0005)	(0.0021)	(0.0008)	(0.0010)	(0.0007)	(0.0021)
ATT (t)	-0.0044	-0.0005	0.0001	0.0000	0.0014	0.0004	-0.0025
	(0.0030)	(0.0005)	(0.0023)	(0.0008)	(0.0011)	(0.0007)	(0.0022)
ATT (t+1)	-0.0062*	-0.0001	-0.0004	0.0007	0.0019	0.0001	-0.0011
	(0.0035)	(0.0006)	(0.0026)	(0.0010)	(0.0014)	(0.0008)	(0.0028)
ATT (t+2)	-0.0059	0.0000	0.0001	0.0013	0.0033**	-0.0001	0.0001
	(0.0036)	(0.0007)	(0.0028)	(0.0012)	(0.0014)	(0.0011)	(0.0030)
ATT (t+3)	-0.0104**	-0.0005	-0.0044	0.0002	0.0059***	-0.0006	0.0116***
	(0.0046)	(0.0009)	(0.0034)	(0.0014)	(0.0022)	(0.0009)	(0.0044)
ATT (t+4)	-0.0324***	-0.0016	0.0027	0.0004	0.0057*	0.0063**	0.0211**
	(0.0091)	(0.0019)	(0.0068)	(0.0023)	(0.0034)	(0.0025)	(0.0095)
ATT (t+5)	-0.0369**	-0.0048*	0.0075	0.0036	0.0042	-0.0003	0.0277*
	(0.0151)	(0.0028)	(0.0107)	(0.0041)	(0.0042)	(0.0028)	(0.0148)
ATT (average)	-0.0097***	-0.0006	-0.0003	0.0007	0.0032***	0.0005	0.0040
	(0.0032)	(0.0006)	(0.0023)	(0.0010)	(0.0012)	(0.0007)	(0.0028)
Test on pre-trend (Chi sq.)	6.4727	13.5927	14.5589	9.9840	24.7690	10.7889	13.4231
p-value	0.7741	0.1924	0.1490	0.4419	0.0058	0.3742	0.2010
Unweighted average	0.2598	0.0242	0.0736	0.0178	0.0189	0.0075	0.0374
Weighted average	0.1847	0.0284	0.0613	0.0177	0.0161	0.0059	0.0279
N. of observations	27,164	27,157	27,164	27,157	27,157	27,157	27,156

Note. The dependent variable is expressed as the share of total expenditure. Estimates are obtained using the doubly robust difference-in-differences estimator, combining stabilized inverse probability weighting with OLS, applied to the sample of not-yet-treated municipalities. Standard errors are shown in parentheses. Statistical significance is indicated as follows * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Breakdown of expenditure by Mission (part II)

	Sustainable development	Transport	Civil relief	Social policies	Economic development	Third-party services
ATT (t-4)	0.0093	-0.0009	0.0006	-0.0040	-0.0031**	-0.0211
	(0.0087)	(0.0072)	(0.0011)	(0.0052)	(0.0014)	(0.0142)
ATT (t-3)	-0.0021	-0.0020	-0.0008	-0.0018	-0.0003	0.0026
	(0.0058)	(0.0057)	(0.0007)	(0.0030)	(0.0011)	(0.0058)
ATT (t-2)	0.0016	0.0029	-0.0025***	0.0018	-0.0008	0.0004
	(0.0025)	(0.0026)	(0.0009)	(0.0015)	(0.0011)	(0.0032)
ATT (t-1)	0.0024	0.0015	0.0006	-0.0030**	0.0002	-0.0011
	(0.0023)	(0.0025)	(0.0009)	(0.0014)	(0.0007)	(0.0032)
ATT (t)	-0.0003	0.0057*	0.0013	-0.0016	0.0007	0.0032
	(0.0026)	(0.0030)	(0.0008)	(0.0014)	(0.0006)	(0.0031)
ATT (t+1)	0.0063**	-0.0010	0.0036**	-0.0005	0.0002	0.0077*
	(0.0031)	(0.0030)	(0.0016)	(0.0019)	(0.0007)	(0.0042)
ATT (t+2)	0.0087***	0.0019	0.0029**	0.0023	0.0002	0.0059
	(0.0033)	(0.0034)	(0.0011)	(0.0019)	(0.0007)	(0.0042)
ATT (t+3)	0.0103**	-0.0006	0.0029*	-0.0013	0.0014	0.0043
	(0.0046)	(0.0039)	(0.0015)	(0.0027)	(0.0009)	(0.0060)
ATT (t+4)	0.0140	-0.0059	0.0021	0.0040	0.0022	0.0090
	(0.0087)	(0.0072)	(0.0025)	(0.0063)	(0.0017)	(0.0125)
ATT (t+5)	0.0154	-0.0043	0.0027	0.0090	0.0125***	0.0003
	(0.0146)	(0.0122)	(0.0051)	(0.0095)	(0.0027)	(0.0199)
ATT (average)	0.0069**	0.0008	0.0026**	0.0004	0.0012*	0.0054
	(0.0030)	(0.0028)	(0.0010)	(0.0020)	(0.0006)	(0.0043)
Test on pre-trend (Chi sq.)	8.1602	10.5829	26.5959	15.4840	13.5711	16.0809
p-value	0.6132	0.3909	0.0030	0.1154	0.1935	0.0973
Unweighted average	0.1405	0.0922	0.0094	0.0801	0.0066	0.1420
Weighted average	0.1389	0.0727	0.0075	0.0904	0.0077	0.2118
N. of observations	27,157	27,157	27,157	27,157	27,157	27,157

Note. The dependent variable is expressed as the share of total expenditure. Estimates are obtained using the doubly robust difference-in-differences estimator, combining stabilized inverse probability weighting with OLS, applied to the sample of not-yet-treated municipalities. Standard errors are shown in parentheses. Statistical significance is indicated as follows * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Three missions account for the majority of the additional fiscal space created by disaster-related transfers:

- Civil relief and emergency management: The budget share allocated to this mission increases by an average of 0.26 p.p., with positive effects observed throughout the five-year post-disaster window and peaking at 0.36 p.p. in $t+2$.
- Sustainable development: Municipal governments allocate an additional 0.69 p.p. of their budgets to this mission on average, with effects emerging in the immediate aftermath and persisting in subsequent years. This finding supports the idea of natural hazards as "windows of opportunity" for climate-resilient investment (Noy and Edmonds, 2019).
- Economic development and competitiveness: Although the average effect is smaller (0.12 p.p.), the increase becomes economically meaningful over time, reaching over 1 p.p. by year five. These funds typically support business recovery initiatives and local labor-market interventions.

Other notable reallocations include modest increases in spending on youth, sport and leisure and spatial planning and housing, consistent with the need to rehabilitate community facilities and update land-use regulations. By contrast, expenditure on institutional and general services declines. The nearly one-percentage-point reduction in general services suggests a deliberate de-prioritisation of routine administrative functions in favour of disaster-related expenditures.

For most other missions, such as education, protection of cultural heritage and social policies, the estimated effects are small, inconsistent across years, and often statistically insignificant. This suggests that core welfare functions are largely insulated from post-disaster reallocations, reinforcing the view that local governments pursue a targeted approach to fiscal adjustment rather than indiscriminate reshuffling.

Taken together, the revenue and expenditure results reveal a consistent pattern of adaptive fiscal behavior. Post-disaster transfers expand the overall budget envelope and, importantly, are often earmarked for specific purposes, steering municipal governments toward investment-oriented spending on reconstruction, risk reduction and local economic revitalisation. To accommodate this reallocation, municipal governments tend to scale back lower-priority or less flexible categories, such as administrative overheads, while largely preserving core social services (Capuno et al., 2024).

The scale and persistence of these compositional adjustments indicate that hydrogeological shocks are not simply short-lived fiscal disturbances. Rather, they trigger lasting transformations in how local governments mobilise and allocate resources in pursuit of developmental objectives. Crucially, as discussed earlier, the capacity to sustain such shifts is not uniform across municipal governments. It depends on their underlying fiscal conditions, a question we explore next in the next section.

5.3 The role of fiscal resilience

Having established sizeable average effects, we now turn to the question: which municipal governments are able to sustain post-disaster spending increases, and why? Our hypothesis is that fiscal capacity at the onset of the shock plays a key role in shaping the response.

As discussed, we proxy this capacity using two structural ratios, measured in 2016 (i.e., prior to any disaster declarations): (i) debt service, defined as the ratio of interest payments to current revenue, and (ii) tax autonomy, the share of own taxes in current revenue.[8]

We begin by examining each dimension separately (Figure 5; Table A.12), before turning to a joint classification (Figure 6; Table A.14) that yields to our four-way typology of fiscal resilience.

Municipal governments with low debt burden (top panel of Figure 5) display a rapid and sustained increase in post-disaster expenditure. Statistically significant effects emerge already in the disaster year and build steadily over time, culminating in a 28.8% increase five years after the event (average ATT: 10.3%). In contrast, high-debt municipalities exhibit a muted and delayed response: treatment effects remain close to zero in the first two years and reach just 15.4% by year five (average ATT: 2.7%, not statistically significant). This divergence highlights the restrictive role of debt servicing obligations, which appear to crowd out fiscal space needed to absorb and deploy disaster-related transfers.

Turning to tax autonomy (bottom panel of Figure 5), we observe that municipal governments with strong own-revenue capacity demonstrate a more sustained expenditure path over time. While their initial spending increase is modest, the effect amplifies in later years, reaching 33.7% by year five (average ATT: 5.8%). By contrast, municipal governments with low autonomy react more immediately, possibly due to reliance on incoming transfers, but plateau sooner and fail to extend the expansion over time (average ATT: 4.0%). These patterns suggest that tax autonomy facilitates the consolidation and continuation of post-disaster investments beyond the initial reconstruction phase.

Figure 6 cross-classifies municipal governments based on both debt burden and tax autonomy, producing four resilience categories. This typology reveals deeper insight into the interaction between fiscal constraints and adaptive capacity:

- Resilient (Low debt & High autonomy): These municipal governments exhibit a gradual but steady post-disaster expansion, peaking five years after the shock (30.5%) with an average ATT (6.6%). Their ability to combine discretionary revenue capacity with manageable debt levels enables a stable recovery trajectory.

- Low debt & Weak autonomy: Despite lacking revenue flexibility, these municipal governments record the largest average ATT (13.8%). Their strong initial response suggests that unconstrained by debt, they can swiftly absorb intergovernmental transfers, though this may reflect reliance rather than self-sufficiency.

- High debt & High autonomy: Initially inert, these municipal governments eventually converge with the resilient core. Significant effects materialize only after three years, indicating that revenue autonomy can compensate for debt-related rigidity, albeit with delay (average ATT: 6.3%).

- Vulnerable (High debt & Low autonomy): This group shows no meaningful fiscal response at any horizon. The lack of both fiscal space and discretion leaves these municipal governments structurally unable to adapt to disaster shocks (average ATT: –0.6%).

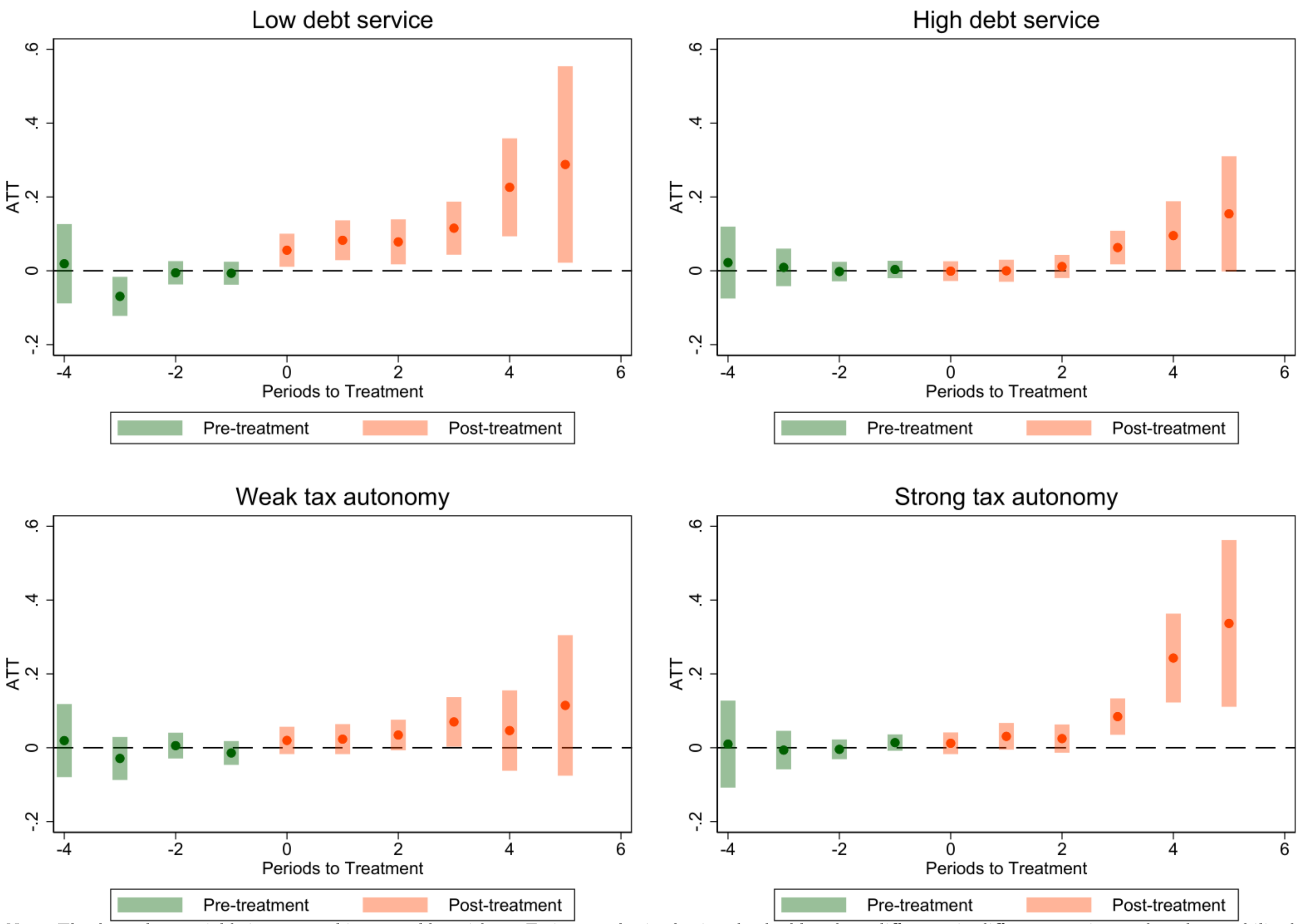
[8] Both indicators are predetermined with respect to the treatment window, mitigating concerns of endogeneity. Using the 2016 cross-section avoids any mechanical feedback from post-disaster transfers to the fiscal space classification.

Two findings emerge. First, debt burden imposes a binding constraint in the short term: municipal governments with high interest obligations are slow to respond, even when they possess strong revenue tools. Second, tax autonomy shapes the medium-term trajectory: among municipal governments with low-debt, autonomy prolongs and strengthens the recovery; among high-debt ones, it tempers rigidity but cannot fully offset it.

These results reinforce the core premise of the paper: fiscal resilience is a measurable determinant of adaptive capacity. While central government transfers are the principal catalyst of post-disaster fiscal expansions, their effectiveness is mediated by local fiscal structures. In this sense, resilience is not merely an institutional ideal but a quantifiable and actionable condition for disaster response.

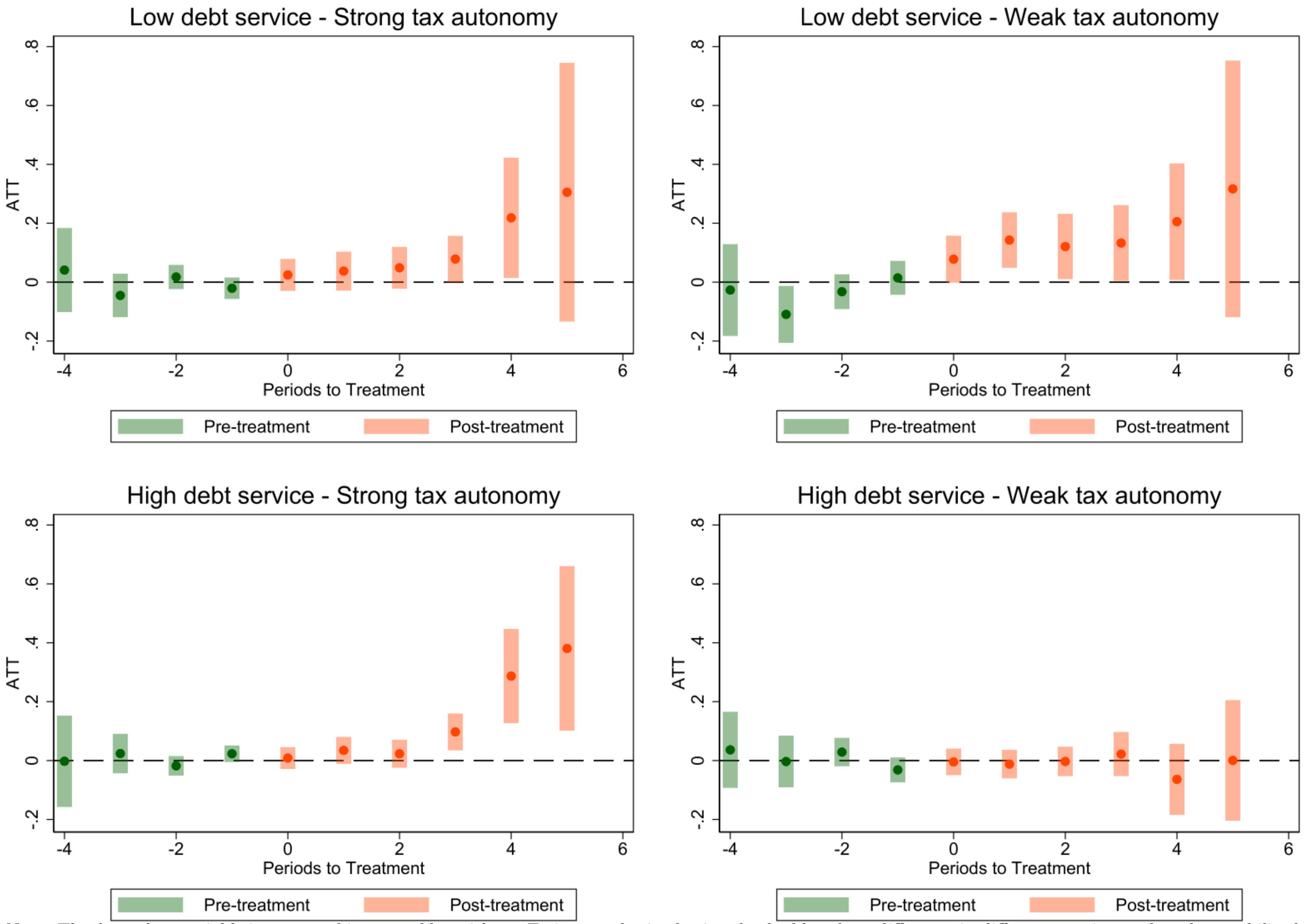
The next section evaluates the robustness of these findings through a series of sensitivity checks, while a broader discussion of their policy implications is provided in the conclusion.

Figure 5: Dynamic effects on total expenditure by initial debt burden and tax autonomy



Note. The dependent variable is expressed in natural logarithms. Estimates obtained using the doubly robust difference-in-differences estimator based on stabilized inverse probability weighting and OLS on the sample of not yet treated municipalities. 95% confidence intervals are shown.

Figure 6: Dynamic effects on total expenditure by fiscal resilience



Note. The dependent variable is expressed in natural logarithms. Estimates obtained using the doubly robust difference-in-differences estimator based on stabilized inverse probability weighting and OLS on the sample of not yet treated municipalities. 95% confidence intervals are shown.

5.4 Robustness and sensitivity analyses

To assess the validity of our baseline estimates and the credibility of the underlying causal claims, we conduct a battery of robustness and sensitivity checks, whose results are reported in Appendix C. These exercises cover a range of empirical strategies, including alternative estimators, leave-one-out procedures, placebo interventions and exposure heterogeneity. Across all approaches, the core conclusion is unaffected: floods and landslides induce a substantial and persistent rise in municipal *capital* expenditure, primarily financed through increased capital revenue inflows, while *current* expenditure remains essentially stable.

5.4.1 Alternative estimators

Appendix C.1 replicates the analysis using five widely used difference-in-differences estimators: two doubly-robust specifications with and without covariate matching, the improved DR estimator of Sant'Anna and Zhao (2020), a pure outcome regression model and inverse-probability weighting with stabilized weights. Across specifications and samples, the average ATT lies between 0.028 and 0.049 for total expenditure (Tables C.1-C.2), 0.037 and 0.058 for total revenue (Tables C.3-C.4), hovers around zero for current expenditure (Tables C.5-C.6) and ranges between 0.053 and 0.173 for capital expenditure (Tables C.7-C.8). Dynamic profiles are virtually identical across estimators and control groups, and pre-trend tests consistently fail to reject parallel trends (all p-values >0.10), underscoring the robustness of the main results.

5.4.2 Leave-one-out and regional exclusion

To assess the sensitivity of our main results to specific disaster episodes and regional composition, Appendix C.2 implements a series of jackknife diagnostics for the two primary dependent variables: total expenditure and total revenue. First, we exclude one treated cohort at a time (i.e., one disaster year) and re-estimate the ATT. As shown in Figures C.1–C.2, the resulting point estimates differ from the baseline by no more than 0.006 log-points and remain well within the 95% confidence interval of the full-sample estimate. Second, we iteratively omit one region from the estimation sample, including each *Regione a Statuto Speciale*, which operates under distinct fiscal arrangements, and re-estimate the model. Figures C.3–C.4 show that the ATT estimates remain stable and statistically indistinguishable from the baseline, reinforcing that our results are not driven by any single event or region.

5.4.3 Placebo interventions

Appendix C.3 presents two placebo exercises designed to assess whether the estimated treatment effects reflect genuine fiscal responses rather than spurious dynamics or incidental timing. First, we extend the event window by five additional years beyond the actual treatment horizon and estimate dynamic effects over this artificially prolonged period. As shown in Figures C.5-C.6, the coefficients for both total expenditure and total revenue rapidly taper off and become statistically indistinguishable from zero, consistent with the absence of any true treatment. Second, we assign each municipality a randomly selected pseudo-treatment year between 2017 and 2021, ensuring no actual disaster occurred during this interval, and re-estimate the model. Figures C.7-C.8 reveal that the resulting effects fluctuate randomly around zero and lack statistical significance throughout the dynamic horizon. Together, these tests reinforce the internal validity of our identification strategy by confirming that the observed treatment effects are not driven by random shocks, calendar-year effects, or residual trends in the data.

5.4.4 Heterogeneous exposure intensity

Appendix C.4 examines whether fiscal responses vary depending on whether a municipality experiences its first or a subsequent declaration of State of Emergency. The sample is stratified by exposure sequence, and dynamic ATT are estimated using both not-yet-treated and ever-treated control groups (Figures C.9–C.12). The first declaration replicates the pronounced and persistent increase in capital outlays observed in Section 5, accompanied by a similar trajectory in revenue. In contrast, the second declaration produces coefficients that are modest in size and consistently lack statistical significance across both outcomes. This attenuated marginal response is consistent with the institutional design of Italy's disaster financing framework. The initial declaration triggers a multi-year reconstruction plan and typically exhausts the municipality's per-capita grant ceiling. As a result, subsequent emergencies are generally absorbed within the pre-funded allocation rather than financed through additional appropriations. In this context, fiscal adjustment involves substantial fixed costs but limited marginal costs, suggesting that our baseline effects primarily reflect a one-time, front-loaded budgetary shift rather than the cumulative impact of repeated shocks.

Across the full range of robustness checks, comprising 40 estimator–sample combinations, 20 jackknife replications, and 8 placebo tests, the results consistently point in the same direction. The magnitude, timing, and composition of the estimated effects remain remarkably stable across specifications, reaffirming the main finding: hydrogeological disasters prompt a sustained, investment-focused expansion of municipal budgets, with no measurable impact on current expenditure. These patterns offer strong empirical validation for the interpretation advanced in Section 5.

6 Conclusions

This study provides robust evidence that climate-induced floods and landslides significantly alter the fiscal trajectory of Italian municipal governments, producing effects that are both substantial in scale and persistent over time. Leveraging a comprehensive panel of accrual-based municipal budgets from 2016 to 2022 and exploiting variation in the timing of official emergency declarations, we document a sharp increase in both total revenues and total expenditures following disaster exposure. However, current spending remains largely unaffected. The fiscal expansion is driven primarily by capital transfers from higher tiers of government and is channelled almost exclusively into investment expenditures, particularly for civil protection, sustainable development and economic development. In contrast, routine administrative services see a slight relative contraction, while key welfare and education functions remain protected.

A central contribution of this paper is the development of an operational measure of fiscal resilience, grounded in two ex-ante structural attributes: the share of debt service in the ordinary budget and the degree of tax autonomy. Their interaction reveals a strong sorting mechanism. Municipal governments that combine low debt service obligations with a high share of autonomous revenue are not only quicker to absorb external transfers but also sustain elevated investment levels for up to five years post-disaster. When only one of these structural pillars is weak, the fiscal response becomes modest or short-lived. When both are lacking, the response vanishes altogether. In the short term, high debt service constitutes the main constraint by limiting co-financing capacity for new projects. In the medium term, low tax autonomy emerges as more binding, as it restricts the ability to maintain fiscal balance once earmarked transfers subside. These asymmetries highlight that identical climate shocks can trigger vastly different recovery paths depending on the underlying financial structure of the affected municipality.

The policy implications are straightforward. Fiscal resilience must be placed on equal footing with engineering and land-use planning in national climate adaptation strategies. First, expanding the local tax base and granting greater discretion over tax instruments can empower municipal governments to complement external transfers without jeopardising core services. Second, emergency transfers should be disbursed through fast and transparent procedures, ensuring that financially weaker municipal governments are not disadvantaged by bureaucratic delays or negotiation asymmetries (Richert et al., 2019; Welsch et al., 2022). Third, capacity-building is crucial. Access to large-scale reconstruction funds hinges on technical capabilities in project design, procurement, and monitoring, skills that are often scarce in smaller local governments. Financial support should thus be paired with institutional support to ensure that resources are absorbed effectively and equitably (Reaños, 2021).

Several promising avenues for future research emerge. High-frequency treasury data could disentangle short-term liquidity support from longer-term investment flows, shedding light on the temporal structure of public responses. Linking budget data to project-level information could help assess whether post-disaster investment contributes to climate adaptation or simply restores pre-disaster conditions. Finally, integrating fiscal trajectories with outcomes such as employment and firm dynamics would allow for a more complete assessment of the socio-economic footprint of local public finance under climate stress.

In sum, effective climate adaptation is not solely about constructing higher levees or more robust bridges. It is equally about strengthening fiscal institutions. In a warming world, local fiscal space and institutional agility are essential public goods and should be treated as critical components of national resilience strategies.

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Appendices (FOR ONLINE PUBLICATION ONLY)

A Additional figures and tables

Table A.1: Summary of significant flooding events in the dataset

Event	**Date**	**Reference**
Flooding in Liguria and Piemonte	Nov. 2016	https://polaris.irpi.cnr.it/event/alluvione-liguria-e-piemonte
Flooding in Livorno	Sep. 2017	https://polaris.irpi.cnr.it/event/alluvione-livorno
Flooding in Emilia-Romagna	Dec. 2017	https://polaris.irpi.cnr.it/event/alluvione-a-lentigione-brescello-pr
Flash flood of Raganello (Calabria)	Aug. 2018	https://polaris.irpi.cnr.it/event/piena-improvvisa-del-torrente-raganello-civita-cs-2
Flooding in Calabria	Oct. 2018	https://polaris.irpi.cnr.it/event/alluvione-in-calabria
Bad weather in Italy	Oct. 2018	https://polaris.irpi.cnr.it/event/maltempo-in-italia
Flood in Sicily	Nov. 2018	https://polaris.irpi.cnr.it/event/alluvione-in-sicilia
Floods in Emilia-Romagna	Jan. 2019	https://polaris.irpi.cnr.it/event/esondazioni-in-emilia-romagna
Disasters in the province of Lecco	Jun. 2019	https://polaris.irpi.cnr.it/event/dissesti-in-provincia-di-lecco
Flood in northern Italy	Oct. 2019	https://polaris.irpi.cnr.it/event/evento-alluvionale-nel-nord-italia
Flood in north-central Italy	Nov. 2019	https://polaris.irpi.cnr.it/event/evento-alluvionale-in-italia-centro-settentrionale
Flood in northwestern Italy	Nov. 2019	https://polaris.irpi.cnr.it/event/evento-alluvionale-in-italia-nord-occidentale
Flood in Liguria and Piemonte	Oct. 2020	https://polaris.irpi.cnr.it/event/evento-alluvionale-in-liguria-e-piemonte
Bitti Flood (NU)	Nov. 2020	https://polaris.irpi.cnr.it/event/alluvione-di-bitti-nu
Flood in Sicily and Calabria	Oct. 2021	https://polaris.irpi.cnr.it/event/evento-alluvionale-in-sicilia-e-calabria
Flood in the Marche region	Sep. 2022	https://polaris.irpi.cnr.it/event/alluvione-nelle-marche

Note. This table lists the main hydrogeological events included in the analysis, based on data from the CNR-IRPI Polaris database. Each entry corresponds to a major flooding episode that affected one or more Italian municipalities between 2016 and 2022. Hyperlinks refer to the official event documentation.

Table A.2: Number of municipalities covered by hydrogeological States of Emergency, by region and year (2016-2022)

Region	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Total**
Abruzzo	0	0	0	19	0	0	0	19
Basilicata	0	28	0	2	0	0	1	31
Calabria	116	0	16	119	3	0	0	254
Campania	0	0	0	70	10	0	2	82
Emilia–Romagna	57	187	44	34	3	0	2	327
Friuli-Venezia Giulia	0	214	1	0	0	0	0	215
Lazio	9	0	65	120	0	0	0	194
Liguria	108	0	83	30	1	1	0	223
Lombardia	80	0	158	194	48	117	0	597
Marche	0	0	0	15	0	0	19	34
Molise	0	117	0	0	0	0	0	117
Piemonte	41	0	3	585	203	5	0	837
Puglia	16	129	0	22	0	0	0	167
Sardegna	0	0	45	0	1	0	0	46
Sicilia	0	5	83	58	0	98	14	258
Toscana	0	3	143	100	0	0	0	246
Trentino–Alto Adige	0	0	81	0	1	0	0	82
Umbria	0	0	0	0	0	0	12	12
Valle d'Aosta	0	13	0	0	14	0	0	27
Veneto	0	57	180	16	32	0	0	285
Total	427	753	902	1384	316	221	50	4,053

Note. Figures report the number of municipalities included in hydrogeological State of Emergency decrees in each year, by region. A municipality affected in multiple years contributes once to each year's total.

Table A.3: Structure of Italian municipal budget: Titles and Missions

Revenue		
Title	**Description**	**Typology**
T1	Current revenue (tax and contributions)	101-104, 301
T2	Current transfers	101-105
T3	Extra-tax revenue	100,200,300,400,500
T4	Capital revenue	100,200,300,400,500
T5	Revenues from the sale of financial assets	100,200,300,400
T6	Borrowing	100,200,300,400
T7	Cash advances	100
T9	Revenue on behalf of third parties	100-200
Expenditure		
Mission	**Description**	**Programs**
M1	Institutional and general services	01-12
M2	Justice	01-03
M3	Public order and security	01-03
M4	Education	01-08
M5	Protection of cultural heritage	01-03
M6	Youth, sport and leisure	01-03
M7	Tourism	01-02
M8	Spatial planning and housing	01-03
M9	Sustainable development	01-09
M10	Transportation and mobility	01-06
M11	Civil relief	01-03
M12	Social policies and family	01-11
M13	Health protection	01-08
M14	Economic development	01-05
M15	Employment and training	01-04
M16	Agriculture and fisheries	01-03
M17	Energy	01-02
M18	Inter-municipal relations	01-02
M19	International relations	01-02
M20	Funds and provisions	01-03
M50	Public debt	01-02
M60	Financial advances	01
M99	Third-party services	01-02

Note. Budget classifications are defined according to E.U. accounting regulations and harmonized national standards, as established by D.Lgs. 118/2011 and 126/2014. Municipal budgets include both provisional and final figures, reported on both cash and accrual bases, and structured according to standard E.U.-compliant classifications (Rossi, 2015).

Table A.4: Summary statistics of key variables

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Population	4,136	6,165.81	22,790.71	0.00	961,011.00
Mean taxable income (€/capita)	4,014	17,495.60	3,887.35	8,020.91	45,711.05
Municipal admin. quality (MAQI)	4,092	103.69	3.51	87.43	114.94
Population density (inh./km^2)	3,992	366.14	794.57	1.06	12,099.95
Near the coast (lit) (0/1)	4,139	0.07	0.25	0.00	1.00
Coastal municipality (cost) (0/1)	4,139	0.14	0.35	0.00	1.00
Urban classification (1–3)	4,139	2.59	0.56	1.00	3.00
Resilience index (0/1)	3,992	0.54	0.14	0.04	1.00
Vulnerability index (0/1)	3,992	0.48	0.13	0.15	1.00
Flood hazard index (0/1)	3,992	0.05	0.10	0.00	1.00
Landslide hazard index (0/1)	3,992	0.09	0.17	0.00	1.00
Public debt expenditure / curr. rev.	2,837	0.02	0.02	0.00	0.15
Tax revenue / total rev.	3,925	0.61	0.19	0.02	0.96

Note. Summary statistics refer to Italian municipalities in 2016. All continuous variables are reported at the municipal level; binary indicators take values between 0 and 1.

Table A.5: Pre-disaster averages of municipal governments' budget: totals and composition shares

Budget Totals (Million Euros)				
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min–Max**
Total expenditure	8,284	11.50	101.00	0.00 – 4,520.00
Total revenues	8,285	12.20	106.00	0.00 – 4,580.00
Total capital expenditure	8,285	1.66	7.74	0.04 – 347.00
Total current expenditure	8,285	5.74	38.20	0.00 – 1,270.00
Revenue composition (shares)				
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min–Max**
T1. Current revenue	7,933	0.389	0.171	0.011 – 0.845
T2. Current transfers	7,933	0.118	0.118	0.000 – 0.840
T3. Extra-tax revenue	7,933	0.125	0.086	0.003 – 0.713
T4. Capital revenue	7,933	0.183	0.156	0.000 – 0.944
T9. Revenue on behalf of third parties	7,933	0.132	0.094	0.000 – 0.819
Expenditure composition (shares)				
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min–Max**
M1. Institutional and general services	7,933	0.264	0.109	0.020 – 0.890
M3. Public order and security	7,932	0.024	0.022	0.000 – 0.316
M4. Education	7,933	0.079	0.067	0.000 – 0.553
M5. Protection of cultural heritage	7,932	0.018	0.032	0.000 – 0.654
M6. Youth, sport and leisure	7,932	0.020	0.033	0.000 – 0.686
M7. Tourism	7,932	0.008	0.025	0.000 – 0.626
M8. Spatial planning and housing	7,931	0.036	0.067	0.000 – 0.714
M9. Sustainable development	7,932	0.140	0.080	0.000 – 0.740
M10. Transportation and mobility	7,932	0.093	0.076	0.000 – 0.685
M11. Civil relief	7,932	0.006	0.032	0.000 – 0.892
M12. Social policies and family	7,932	0.075	0.069	0.000 – 0.696
M14. Economic development	7,932	0.006	0.023	0.000 – 0.623
M50. Public debt	7,932	0.037	0.032	0.000 – 0.356
M99. Third-party services	7,932	0.138	0.097	0.000 – 0.825

Note. This table reports descriptive statistics for municipal government budgets during the pre-disaster period. Budget totals are expressed in millions of Euros and include total, current and capital expenditures as well as total revenues. Composition shares indicate the proportion of each revenue Title or expenditure Mission relative to the corresponding annual total.

Table A.6: Breakdown of revenue by title (not yet treated)

	Current revenue	**Current transfers**	**Extra-tax revenue**	**Capital revenue**	**Revenue on behalf of third parties**
ATT (t-4)	0.0029	-0.0001	-0.0012	0.0022	-0.0159
	(0.0122)	(0.0081)	(0.0082)	(0.0186)	(0.0139)
ATT (t-3)	0.0031	-0.0022	-0.0049	0.0008	0.0006
	(0.0073)	(0.0042)	(0.0039)	(0.0106)	(0.0057)
ATT (t-2)	-0.0047	-0.0011	-0.0011	0.0073	-0.0019
	(0.0035)	(0.0020)	(0.0020)	(0.0051)	(0.0032)
ATT (t-1)	0.0065**	-0.0014	0.0003	-0.0033	0.0006
	(0.0033)	(0.0020)	(0.0017)	(0.0049)	(0.0030)
ATT (t)	-0.0072**	-0.0042*	-0.0032*	0.0155**	0.0024
	(0.0035)	(0.0022)	(0.0018)	(0.0055)	(0.0031)
ATT (t+1)	-0.0126***	-0.0018	-0.0021	0.0164**	0.0053
	(0.0038)	(0.0026)	(0.0021)	(0.0059)	(0.0040)
ATT (t+2)	-0.0124**	-0.0076***	-0.0014	0.0309***	0.0046
	(0.0045)	(0.0029)	(0.0023)	(0.0063)	(0.0040)
ATT (t+3)	-0.0163**	-0.0030	-0.0057**	0.0393***	0.0053
	(0.0059)	(0.0043)	(0.0027)	(0.0085)	(0.0057)
ATT (t+4)	-0.0257**	-0.0247***	-0.0117**	0.0604***	0.0168
	(0.0119)	(0.0078)	(0.0052)	(0.0164)	(0.0120)
ATT (t+5)	-0.0327*	-0.0430***	-0.0293***	0.1171***	0.0069
	(0.0191)	(0.0139)	(0.0087)	(0.0277)	(0.0192)
ATT (average)	-0.0138***	-0.0073**	-0.0048**	0.0310***	0.0053
	(0.0042)	(0.0029)	(0.0020)	(0.0059)	(0.0041)
Test on pre-trend (Chi sq.)	28.3960	10.5758	7.6938	22.8318	12.1117
p-value	0.0016***	0.3915	0.6587	0.0114**	0.2777
Unweighted average	0.3775	0.1389	0.1173	0.1810	0.1344
Weighted average	0.3496	0.1211	0.1075	0.1298	0.1954
N. of observations	27,164	27,164	27,164	27,163	27,164

Note. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are based on the doubly robust difference-in-differences estimator of (Sant'Anna and Zhao, 2020), combining stabilized inverse probability weighting with ordinary least squares regression.

Table A.7: Breakdown of revenue by title (never treated)

	Current revenue	**Current transfers**	**Extra-tax revenue**	**Capital revenue**	**Revenue on behalf of third parties**
ATT (t-4)	0.0029	-0.0001	-0.0012	0.0022	-0.0159
	(0.0122)	(0.0081)	(0.0082)	(0.0186)	(0.0139)
ATT (t-3)	0.0037	-0.0019	-0.0047	0.0001	0.0002
	(0.0073)	(0.0042)	(0.0039)	(0.0105)	(0.0057)
ATT (t-2)	-0.0043	-0.0016	-0.0013	0.0072	-0.0022
	(0.0035)	(0.0021)	(0.0020)	(0.0051)	(0.0032)
ATT (t-1)	0.0062*	-0.0015	0.0000	-0.0027	0.0001
	(0.0033)	(0.0020)	(0.0017)	(0.0049)	(0.0030)
ATT (t)	-0.0068*	-0.0033	-0.0032*	0.0142**	0.0024
	(0.0033)	(0.0021)	(0.0017)	(0.0052)	(0.0029)
ATT (t+1)	-0.0129***	-0.0010	-0.0022	0.0163**	0.0048
	(0.0037)	(0.0024)	(0.0020)	(0.0056)	(0.0037)
ATT (t+2)	-0.0126**	-0.0070**	-0.0014	0.0306***	0.0040
	(0.0044)	(0.0028)	(0.0022)	(0.0062)	(0.0039)
ATT (t+3)	-0.0160**	-0.0027	-0.0055**	0.0378***	0.0052
	(0.0057)	(0.0041)	(0.0026)	(0.0082)	(0.0056)
ATT (t+4)	-0.0257**	-0.0247***	-0.0117**	0.0604***	0.0168
	(0.0119)	(0.0078)	(0.0052)	(0.0164)	(0.0120)
ATT (t+5)	-0.0327*	-0.0430***	-0.0293***	0.1171***	0.0069
	(0.0191)	(0.0139)	(0.0087)	(0.0277)	(0.0192)
ATT (average)	-0.0137***	-0.0067**	-0.0047**	0.0304***	0.0051
	(0.0041)	(0.0028)	(0.0020)	(0.0057)	(0.0040)
Test on pre-trend (Chi sq.)	27.3485	12.9050	7.7817	22.7047	13.4029
p-value	0.0023***	0.2290	0.6501	0.0119**	0.2020
Unweighted average	0.3775	0.1389	0.1173	0.1810	0.1344
Weighted average	0.3496	0.1211	0.1075	0.1298	0.1954
N. of observations	27,154	27,154	27,154	27,153	27,154

Note. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are based on the doubly robust difference-in-differences estimator of (Sant'Anna and Zhao, 2020), combining stabilized inverse probability weighting with ordinary least squares regression.

Table A.8: Breakdown of expenditure by mission (not yet treated) – part 1

	Institutional and general services	**Public order and security**	**Education**	**Protection of cultural heritage**	**Youth, sport and leisure**	**Tourism**	**Spatial planning and housing**
ATT (t-4)	-0.0002	0.0013	0.0104**	0.0011	-0.0016	-0.0042	0.0056
	(0.0097)	(0.0017)	(0.0049)	(0.0027)	(0.0075)	(0.0032)	(0.0053)
ATT (t-3)	-0.0028	0.0020**	-0.0021	-0.0051**	-0.0042	0.0041	0.0005
	(0.0058)	(0.0009)	(0.0035)	(0.0026)	(0.0034)	(0.0027)	(0.0031)
ATT (t-2)	-0.0024	-0.0002	0.0036	-0.0004	-0.0025**	-0.0022	0.0014
	(0.0030)	(0.0006)	(0.0025)	(0.0012)	(0.0013)	(0.0014)	(0.0022)
ATT (t-1)	0.0031	-0.0009*	-0.0033	0.0002	0.0013	0.0009	0.0000
	(0.0027)	(0.0005)	(0.0021)	(0.0008)	(0.0010)	(0.0007)	(0.0021)
ATT (t)	-0.0044	-0.0005	0.0001	0.0000	0.0014	0.0004	-0.0025
	(0.0030)	(0.0005)	(0.0023)	(0.0008)	(0.0011)	(0.0007)	(0.0022)
ATT (t+1)	-0.0062*	-0.0001	-0.0004	0.0007	0.0019	0.0001	-0.0011
	(0.0035)	(0.0006)	(0.0026)	(0.0010)	(0.0014)	(0.0008)	(0.0028)
ATT (t+2)	-0.0059	0.0000	0.0001	0.0013	0.0033**	-0.0001	0.0001
	(0.0036)	(0.0007)	(0.0028)	(0.0012)	(0.0014)	(0.0011)	(0.0030)
ATT (t+3)	-0.0104**	-0.0005	-0.0044	0.0002	0.0059***	-0.0006	0.0116***
	(0.0046)	(0.0009)	(0.0034)	(0.0014)	(0.0022)	(0.0009)	(0.0044)
ATT (t+4)	-0.0324***	-0.0016	0.0027	0.0004	0.0057*	0.0063**	0.0211**
	(0.0091)	(0.0019)	(0.0068)	(0.0023)	(0.0034)	(0.0025)	(0.0095)
ATT (t+5)	-0.0369**	-0.0048*	0.0075	0.0036	0.0042	-0.0003	0.0277*
	(0.0151)	(0.0028)	(0.0107)	(0.0041)	(0.0042)	(0.0028)	(0.0148)
ATT (average)	-0.0097***	-0.0006	-0.0003	0.0007	0.0032***	0.0005	0.0040
	(0.0032)	(0.0006)	(0.0023)	(0.0010)	(0.0012)	(0.0007)	(0.0028)
Test on pre-trend (Chi sq.)	6.4727	13.5927	14.5589	9.9840	24.7690***	10.7889	13.4231
p-value	0.7741	0.1924	0.1490	0.4419	0.0058	0.3742	0.2010
Unweighted average	0.2598	0.0242	0.0736	0.0178	0.0189	0.0075	0.0374
Weighted average	0.1847	0.0284	0.0613	0.0177	0.0161	0.0059	0.0279
N. of observations	27,164	27,157	27,164	27,157	27,157	27,157	27,156

Note. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are based on the doubly robust difference-in-differences estimator of (Sant'Anna and Zhao, 2020), combining stabilized inverse probability weighting with ordinary least squares regression.

Table A.9: Breakdown of expenditure by mission (never treated) – part 1

	Institutional and general services	Public order and security	Education	Protection of cultural heritage	Youth, sport and leisure	Tourism	Spatial planning and housing
ATT (t-4)	-0.0002	0.0013	0.0104**	0.0011	-0.0016	-0.0042	0.0056
	(0.0097)	(0.0017)	(0.0049)	(0.0027)	(0.0075)	(0.0032)	(0.0053)
ATT (t-3)	-0.0032	0.0022**	-0.0023	-0.0050*	-0.0046	0.0036	0.0007
	(0.0059)	(0.0009)	(0.0036)	(0.0026)	(0.0035)	(0.0026)	(0.0032)
ATT (t-2)	-0.0031	0.0000	0.0034	-0.0006	-0.0028**	-0.0018	0.0017
	(0.0029)	(0.0007)	(0.0025)	(0.0012)	(0.0012)	(0.0012)	(0.0022)
ATT (t-1)	0.0031	-0.0008*	-0.0030	0.0001	0.0011	0.0006	0.0001
	(0.0027)	(0.0005)	(0.0021)	(0.0008)	(0.0010)	(0.0007)	(0.0021)
ATT (t)	-0.0037	-0.0005	-0.0001	-0.0003	0.0013	0.0003	-0.0025
	(0.0028)	(0.0005)	(0.0022)	(0.0008)	(0.0011)	(0.0007)	(0.0021)
ATT (t+1)	-0.0060*	-0.0002	-0.0003	0.0003	0.0015	-0.0002	-0.0009
	(0.0033)	(0.0006)	(0.0024)	(0.0010)	(0.0013)	(0.0008)	(0.0027)
ATT (t+2)	-0.0057	0.0000	0.0002	0.0013	0.0030**	0.0000	0.0001
	(0.0035)	(0.0007)	(0.0027)	(0.0012)	(0.0014)	(0.0011)	(0.0030)
ATT (t+3)	-0.0103**	-0.0005	-0.0041	0.0002	0.0056**	-0.0006	0.0114***
	(0.0045)	(0.0009)	(0.0033)	(0.0014)	(0.0022)	(0.0008)	(0.0043)
ATT (t+4)	-0.0324***	-0.0016	0.0027	0.0004	0.0057*	0.0063**	0.0211**
	(0.0091)	(0.0019)	(0.0068)	(0.0023)	(0.0034)	(0.0025)	(0.0095)
ATT (t+5)	-0.0369**	-0.0048*	0.0075	0.0036	0.0042	-0.0003	0.0277*
	(0.0151)	(0.0028)	(0.0107)	(0.0041)	(0.0042)	(0.0028)	(0.0148)
ATT (average)	-0.0094***	-0.0006	-0.0003	0.0005	0.0030***	0.0004	0.0040
	(0.0032)	(0.0006)	(0.0023)	(0.0009)	(0.0011)	(0.0007)	(0.0027)
Test on pre-trend (Chi sq.)	5.9942	14.6198	14.3259	9.8863	24.3113***	10.9609	12.1093
p-value	0.8158	0.1466	0.1586	0.4505	0.0068	0.3606	0.2778
Unweighted average	0.2598	0.0242	0.0736	0.0178	0.0189	0.0075	0.0374
Weighted average	0.1847	0.0284	0.0613	0.0177	0.0161	0.0059	0.0279
N. of observations	27,154	27,147	27,154	27,147	27,147	27,147	27,146

Note. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are based on the doubly robust difference-in-differences estimator of (Sant'Anna and Zhao, 2020), combining stabilized inverse probability weighting with ordinary least squares regression.

Table A.10: Breakdown of expenditure by mission (not yet treated) – part 2

	Sustainable development	**Transportation & mobility**	**Civil relief**	**Social policies & family**	**Economic development**	**Public debt**	**Third-party services**
ATT (t-4)	0.0093	-0.0009	0.0006	-0.0040	-0.0031**	-0.0015	-0.0211
	(0.0087)	(0.0072)	(0.0011)	(0.0052)	(0.0014)	(0.0043)	(0.0142)
ATT (t-3)	-0.0021	-0.0020	-0.0008	-0.0018	-0.0003	0.0013	0.0026
	(0.0058)	(0.0057)	(0.0007)	(0.0030)	(0.0011)	(0.0021)	(0.0058)
ATT (t-2)	0.0016	0.0029	-0.0025***	0.0018	-0.0008	0.0015	0.0004
	(0.0025)	(0.0026)	(0.0009)	(0.0015)	(0.0011)	(0.0010)	(0.0032)
ATT (t-1)	0.0024	0.0015	0.0006	-0.0030**	0.0002	0.0000	-0.0011
	(0.0023)	(0.0025)	(0.0009)	(0.0014)	(0.0007)	(0.0010)	(0.0032)
ATT (t)	-0.0003	0.0057*	0.0013	-0.0016	0.0007	-0.0014	0.0032
	(0.0026)	(0.0030)	(0.0008)	(0.0014)	(0.0006)	(0.0010)	(0.0031)
ATT (t+1)	0.0063**	-0.0010	0.0036**	-0.0005	0.0002	-0.0014	0.0077*
	(0.0031)	(0.0030)	(0.0016)	(0.0019)	(0.0007)	(0.0011)	(0.0042)
ATT (t+2)	0.0087***	0.0019	0.0029**	0.0023	0.0002	-0.0028**	0.0059
	(0.0033)	(0.0034)	(0.0011)	(0.0019)	(0.0007)	(0.0011)	(0.0042)
ATT (t+3)	0.0103**	-0.0006	0.0029*	-0.0013	0.0014	-0.0034**	0.0043
	(0.0046)	(0.0039)	(0.0015)	(0.0027)	(0.0009)	(0.0017)	(0.0060)
ATT (t+4)	0.0140	-0.0059	0.0021	0.0040	0.0022	-0.0091***	0.0090
	(0.0087)	(0.0072)	(0.0025)	(0.0063)	(0.0017)	(0.0028)	(0.0125)
ATT (t+5)	0.0154	-0.0043	0.0027	0.0090	0.0125***	-0.0069	0.0003
	(0.0146)	(0.0122)	(0.0051)	(0.0095)	(0.0027)	(0.0044)	(0.0199)
ATT (average)	0.0069**	0.0008	0.0026**	0.0004	0.0012*	-0.0029***	0.0054
	(0.0030)	(0.0028)	(0.0010)	(0.0020)	(0.0006)	(0.0011)	(0.0043)
Test on pre-trend (Chi sq.)	8.1602	10.5829	26.5959***	15.4840	13.5711	8.7901	16.0809*
p-value	0.6132	0.3909	0.0030	0.1154	0.1935	0.5521	0.0973
Unweighted average	0.1405	0.0922	0.0094	0.0801	0.0066	0.0366	0.1420
Weighted average	0.1389	0.0727	0.0075	0.0904	0.0077	0.0373	0.2118
N. of observations	27,157	27,157	27,157	27,157	27,157	27,157	27,157

Note. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are based on the doubly robust difference-in-differences estimator of (Sant'Anna and Zhao, 2020), combining stabilized inverse probability weighting with ordinary least squares regression.

Table A.11: Breakdown of expenditure by mission (never treated) – part 2

	Sustainable development	**Transportation and mobility**	**Civil relief**	**Social policies and family**	**Economic development**	**Public debt**	**Third-party services**
ATT (t-4)	0.0093	-0.0009	0.0006	-0.0040	-0.0031**	-0.0015	-0.0211
	(0.0087)	(0.0072)	(0.0011)	(0.0052)	(0.0014)	(0.0043)	(0.0142)
ATT (t-3)	-0.0008	-0.0019	-0.0009	-0.0019	-0.0003	0.0014	0.0020
	(0.0052)	(0.0056)	(0.0007)	(0.0030)	(0.0011)	(0.0021)	(0.0058)
ATT (t-2)	0.0016	0.0033	-0.0026***	0.0016	-0.0010	0.0015	0.0000
	(0.0025)	(0.0025)	(0.0009)	(0.0014)	(0.0011)	(0.0010)	(0.0032)
ATT (t-1)	0.0025	0.0015	0.0006	-0.0034**	0.0001	0.0001	-0.0012
	(0.0023)	(0.0024)	(0.0008)	(0.0015)	(0.0007)	(0.0010)	(0.0031)
ATT (t)	-0.0004	0.0057**	0.0011	-0.0012	0.0008	-0.0011	0.0031
	(0.0024)	(0.0028)	(0.0008)	(0.0014)	(0.0006)	(0.0010)	(0.0030)
ATT (t+1)	0.0064**	-0.0008	0.0035**	-0.0003	0.0001	-0.0011	0.0074*
	(0.0029)	(0.0029)	(0.0014)	(0.0017)	(0.0007)	(0.0010)	(0.0039)
ATT (t+2)	0.0084***	0.0020	0.0028**	0.0021	0.0002	-0.0026**	0.0054
	(0.0032)	(0.0033)	(0.0011)	(0.0019)	(0.0007)	(0.0011)	(0.0041)
ATT (t+3)	0.0101**	-0.0004	0.0029**	-0.0013	0.0013	-0.0033**	0.0042
	(0.0044)	(0.0038)	(0.0015)	(0.0026)	(0.0009)	(0.0016)	(0.0059)
ATT (t+4)	0.0140	-0.0059	0.0021	0.0040	0.0022	-0.0091***	0.0090
	(0.0087)	(0.0072)	(0.0025)	(0.0063)	(0.0017)	(0.0028)	(0.0125)
ATT (t+5)	0.0154	-0.0043	0.0027	0.0090	0.0125***	-0.0069	0.0003
	(0.0146)	(0.0122)	(0.0051)	(0.0095)	(0.0027)	(0.0044)	(0.0199)
ATT (average)	0.0068**	0.0009	0.0025**	0.0005	0.0012*	-0.0027**	0.0052
	(0.0029)	(0.0027)	(0.0010)	(0.0019)	(0.0006)	(0.0011)	(0.0041)
Test on pre-trend (Chi sq.)	8.3658	10.0477	26.6693***	16.0573*	12.0696	8.1791	16.8475*
p-value	0.5931	0.4363	0.0029	0.0980	0.2804	0.6114	0.0778
Unweighted average	0.1405	0.0922	0.0094	0.0801	0.0066	0.0366	0.1420
Weighted average	0.1389	0.0727	0.0075	0.0904	0.0077	0.0373	0.2118
N. of observations	27,147	27,147	27,147	27,147	27,147	27,147	27,147

Note. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are based on the doubly robust difference-in-differences estimator of (Sant'Anna and Zhao, 2020), combining stabilized inverse probability weighting with ordinary least squares regression.

Table A.12: Debt service and tax autonomy (not yet treated)

	Low debt service	High debt service	Weak tax autonomy	Strong tax autonomy
ATT (t-4)	0.0191	0.0222	0.0193	0.0098
	(0.0548)	(0.0497)	(0.0505)	(0.0601)
ATT (t-3)	-0.0693**	0.0092	-0.0290	-0.0064
	(0.0270)	(0.0259)	(0.0297)	(0.0266)
ATT (t-2)	-0.0055	-0.0021	0.0057	-0.0043
	(0.0161)	(0.0135)	(0.0178)	(0.0137)
ATT (t-1)	-0.0067	0.0034	-0.0142	0.0139
	(0.0159)	(0.0120)	(0.0165)	(0.0113)
ATT (t)	0.0557**	-0.0010	0.0198	0.0121
	(0.0228)	(0.0137)	(0.0189)	(0.0150)
ATT (t+1)	0.0826***	0.0000	0.0233	0.0308*
	(0.0275)	(0.0152)	(0.0207)	(0.0184)
ATT (t+2)	0.0783**	0.0116	0.0344	0.0247
	(0.0311)	(0.0160)	(0.0212)	(0.0196)
ATT (t+3)	0.1154***	0.0629***	0.0699**	0.0843***
	(0.0367)	(0.0232)	(0.0342)	(0.0252)
ATT (t+4)	0.2260***	0.0952**	0.0465	0.2429***
	(0.0677)	(0.0475)	(0.0556)	(0.0614)
ATT (t+5)	0.2879**	0.1542*	0.1146	0.3367***
	(0.1358)	(0.0796)	(0.0971)	(0.1152)
ATT (average)	0.1026***	0.0266	0.0399*	0.0575***
	(0.0271)	(0.0164)	(0.0232)	(0.0191)
Test on pre-trend (Chi sq.)	16.9277	8.1420	13.9523	13.1520
p-value	0.0760	0.6150	0.1752	0.2153
N. of observations	9,312	17,845	12,573	14,584

Note. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are based on the doubly robust difference-in-differences estimator of (Sant'Anna and Zhao, 2020), combining stabilized inverse probability weighting with ordinary least squares regression.

Table A.13: Debt service and tax autonomy (never treated)

	Low debt service	High debt service	Weak tax autonomy	Strong tax autonomy
ATT (t-4)	0.0191	0.0222	0.0193	0.0098
	(0.0548)	(0.0497)	(0.0505)	(0.0601)
ATT (t-3)	-0.0702**	0.0113	-0.0259	-0.0115
	(0.0271)	(0.0252)	(0.0290)	(0.0294)
ATT (t-2)	-0.0071	0.0009	0.0064	0.0001
	(0.0162)	(0.0132)	(0.0178)	(0.0140)
ATT (t-1)	-0.0061	0.0007	-0.0147	0.0084
	(0.0161)	(0.0118)	(0.0163)	(0.0110)
ATT (t)	0.0465**	0.0028	0.0190	0.0096
	(0.0219)	(0.0128)	(0.0188)	(0.0133)
ATT (t+1)	0.0709***	0.0039	0.0260	0.0261
	(0.0254)	(0.0144)	(0.0208)	(0.0166)
ATT (t+2)	0.0788***	0.0101	0.0336	0.0216
	(0.0297)	(0.0156)	(0.0213)	(0.0186)
ATT (t+3)	0.1141***	0.0605***	0.0678**	0.0826***
	(0.0356)	(0.0225)	(0.0327)	(0.0246)
ATT (t+4)	0.2260***	0.0952**	0.0465	0.2429***
	(0.0677)	(0.0475)	(0.0556)	(0.0614)
ATT (t+5)	0.2879**	0.1542*	0.1146	0.3367***
	(0.1358)	(0.0796)	(0.0971)	(0.1152)
ATT (average)	0.0975***	0.0277*	0.0398*	0.0547***
	(0.0260)	(0.0158)	(0.0233)	(0.0181)
Test on pre-trend (Chi sq.)	16.4636	7.1630	13.4113	15.6529
p-value	0.0871	0.7100	0.2016	0.1100
N. of observations	9,307	17,840	12,567	14,580

Note. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are based on the doubly robust difference-in-differences estimator of (Sant'Anna and Zhao, 2020), combining stabilized inverse probability weighting with ordinary least squares regression.

Table A.14: Fiscal resilience (not yet treated)

	Low debt service, strong autonomy	Low debt service, weak autonomy	High debt service, strong autonomy	High debt service, weak autonomy
ATT (t-4)	0.0410	-0.0268	-0.0025	0.0363
	(0.0728)	(0.0795)	(0.0791)	(0.0660)
ATT (t-3)	-0.0452	-0.1095**	0.0239	-0.0031
	(0.0377)	(0.0493)	(0.0342)	(0.0448)
ATT (t-2)	0.0175	-0.0324	-0.0179	0.0289
	(0.0209)	(0.0302)	(0.0169)	(0.0246)
ATT (t-1)	-0.0207	0.0145	0.0232	-0.0317
	(0.0187)	(0.0294)	(0.0143)	(0.0216)
ATT (t)	0.0246	0.0780*	0.0086	-0.0046
	(0.0277)	(0.0407)	(0.0189)	(0.0230)
ATT (t+1)	0.0375	0.1428***	0.0346	-0.0121
	(0.0338)	(0.0481)	(0.0234)	(0.0247)
ATT (t+2)	0.0488	0.1210**	0.0230	-0.0030
	(0.0362)	(0.0567)	(0.0242)	(0.0255)
ATT (t+3)	0.0785*	0.1331**	0.0973***	0.0220
	(0.0402)	(0.0656)	(0.0319)	(0.0382)
ATT (t+4)	0.2183**	0.2054**	0.2869***	-0.0638
	(0.1043)	(0.1011)	(0.0817)	(0.0616)
ATT (t+5)	0.3054	0.3168	0.3809***	0.0005
	(0.2243)	(0.2223)	(0.1426)	(0.1044)
ATT (average)	0.0660*	0.1377***	0.0626***	-0.0062
	(0.0338)	(0.0458)	(0.0241)	(0.0265)
Test on pre-trend (Chi sq.)	11.9702	20.7080**	11.9072	10.1836
p-value	0.2871	0.0232	0.2913	0.4245
N. of observations	4,933	4,379	9,651	8,194

Note. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are based on the doubly robust difference-in-differences estimator of (Sant'Anna and Zhao, 2020), combining stabilized inverse probability weighting with ordinary least squares regression.

Table A.15: Fiscal resilience (never treated)

	Low debt service, strong autonomy	Low debt service, weak autonomy	High debt service, strong autonomy	High debt service, weak autonomy
ATT (t-4)	0.0410	-0.0268	-0.0025	0.0363
	(0.0728)	(0.0795)	(0.0791)	(0.0660)
ATT (t-3)	-0.0447	-0.1116**	0.0045	0.0067
	(0.0381)	(0.0494)	(0.0343)	(0.0426)
ATT (t-2)	0.0150	-0.0308	-0.0091	0.0286
	(0.0208)	(0.0303)	(0.0172)	(0.0243)
ATT (t-1)	-0.0199	0.0098	0.0142	-0.0306
	(0.0188)	(0.0295)	(0.0142)	(0.0213)
ATT (t)	0.0209	0.0657	0.0084	-0.0015
	(0.0251)	(0.0417)	(0.0168)	(0.0222)
ATT (t+1)	0.0319	0.1214***	0.0300	-0.0077
	(0.0308)	(0.0464)	(0.0211)	(0.0242)
ATT (t+2)	0.0446	0.1171**	0.0202	-0.0038
	(0.0348)	(0.0547)	(0.0229)	(0.0253)
ATT (t+3)	0.0785**	0.1295**	0.0946***	0.0210
	(0.0395)	(0.0622)	(0.0312)	(0.0367)
ATT (t+4)	0.2183**	0.2054**	0.2869***	-0.0638
	(0.1043)	(0.1011)	(0.0817)	(0.0616)
ATT (t+5)	0.3054	0.3168	0.3809***	0.0005
	(0.2243)	(0.2223)	(0.1426)	(0.1044)
ATT (average)	0.0628*	0.1283***	0.0602***	-0.0048
	(0.0326)	(0.0452)	(0.0227)	(0.0260)
Test on pre-trend (Chi sq.)	11.6128	20.1612	12.3997	9.3153
p-value	0.3118	0.0278	0.2592	0.5025
N. of observations	4,932	4,375	9,648	8,192

Note. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are based on the doubly robust difference-in-differences estimator of (Sant'Anna and Zhao, 2020), combining stabilized inverse probability weighting with ordinary least squares regression.

B Balancing of matching

To illustrate the quality of our covariate adjustment, we estimate the propensity score for the subsample of municipalities that were either treated only once during 2017–2022 or never treated throughout 2013–2022. This exercise assesses whether the pool of "pure" counterfactual units, i.e., never-treated municipalities, is sufficiently large and diverse to serve as a valid comparator for the treated group. While our preferred empirical specification also leverages not-yet-treated municipalities as controls, the unmatched comparison provides useful diagnostic insights into the quality of the match.

The propensity score model includes key pre-treatment characteristics that may jointly influence disaster exposure and fiscal outcomes. These include: socio-economic conditions (log population, taxable income, urban classification), institutional quality, environmental exposure (proximity to the coast, flood and landslide hazard indices) and composite indices of disaster resilience and vulnerability.

Table B.1 presents average marginal effects from a probit model for the probability of treatment, alongside standardized differences before and after matching. Matching is performed using nearest neighbour with caliper (one-quarter of the s.d. of the propensity score), imposing a common support condition.

Table B.1: Probit estimates and covariate balance before and after matching

Dep. var.: Pr(Treat)	**Average Marginal Effects AMEs**	**Not matched: t-stat [p-value]**	**Matched: t-stat [p-value]**
Population (log)	0.0767***	-0.09 [0.925]	-0.32 [0.748]
	(0.0122)		
Mean taxable income p.c. (log)	-0.1432*	2.39 [0.017]	1.39 [0.166]
	(0.0880)		
Municipal Admin. Quality	-0.0028	-1.79 [0.074]	1.25 [0.211]
	(0.0027)		
Population density (log)	-0.0700***	-1.77 [0.077]	0.54 [0.590]
	(0.0123)		
Near the coast	0.1389***	3.69 [<0.001]	-0.64 [0.521]
	(0.0475)		
Coastal	0.1169***	2.29 [0.022]	-0.56 [0.577]
	(0.0367)		
Urban	0.0237	1.14 [0.255]	-0.59 [0.555]
	(0.0250)		
Resilience index	-0.8981***	2.81 [0.005]	2.19 [0.029]
	(0.1667)		
Vulnerability index	-0.4757***	-3.92 [<0.001]	-1.69 [0.092]
	(0.1132)		
Flood hazard	-0.0159	2.88 [0.004]	-1.12 [0.263]
	(0.0863)		
Landslide hazard	-0.3726***	-4.74 [<0.001]	-0.32 [0.748]
	(0.0768)		
N.	2,726		
Pseudo R-sq.	0.0594		

Note. Matching based on nearest neighbour with caliper (1/4 SD of propensity score) and common support. Covariates refer to 2016. Treated units are compared to never-treated municipalities. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Several covariates, including geographic, fiscal and institutional characteristics, significantly predict treatment, underscoring the need for careful adjustment. After matching, most standardized differences become statistically insignificant, indicating good covariate balance. Some imbalance persists for the resilience and vulnerability indices, which likely reflect deeper structural or historical features that are difficult to fully align through matching alone.

Overall, the results support the credibility of our matching strategy and the validity of the control group used in the doubly robust difference-in-differences estimator. By substantially reducing observable differences between treated and control municipalities, the matching step strengthens the plausibility of the conditional parallel trends assumption underlying our causal design.

C Robustness tests

C.1 Alternative estimators

Table C.1: Total expenditure (not yet treated)

	Doubly robust DiD based on stabilized inv. prob. weighting and OLS (no matching)	Doubly robust DiD based on stabilized inv. prob. weighting and OLS (with matching)	Improved doubly robust DiD estimator based on inv. prob. of tilting and weighted least squares	Outcome regression DiD estimator based on OLS	Inverse probability weighting DiD estimator with stabilized weights
ATT (t-4)	0.0080	0.0192	0.0131	0.0063	0.0132
	(0.0190)	(0.0374)	(0.0206)	(0.0196)	(0.0375)
ATT (t-3)	-0.0001	-0.0180	-0.0134	-0.0131	-0.0126
	(0.0116)	(0.0180)	(0.0135)	(0.0126)	(0.0180)
ATT (t-2)	-0.0063	-0.0019	-0.0064	-0.0050	-0.0053
	(0.0080)	(0.0102)	(0.0086)	(0.0084)	(0.0103)
ATT (t-1)	0.0114	-0.0004	0.0004	0.0010	0.0003
	(0.0073)	(0.0094)	(0.0078)	(0.0076)	(0.0094)
ATT (t)	0.0036	0.0149	0.0064	0.0069	0.0058
	(0.0073)	(0.0112)	(0.0079)	(0.0078)	(0.0112)
ATT (t+1)	0.0238***	0.0215*	0.0165*	0.0180*	0.0159
	(0.0087)	(0.0128)	(0.0094)	(0.0093)	(0.0129)
ATT (t+2)	0.0375***	0.0290**	0.0211*	0.0258**	0.0212
	(0.0105)	(0.0136)	(0.0111)	(0.0109)	(0.0136)
ATT (t+3)	0.0507***	0.0806***	0.0572***	0.0596***	0.0576***
	(0.0129)	(0.0196)	(0.0136)	(0.0134)	(0.0196)
ATT (t+4)	0.0426**	0.1411***	0.0781***	0.0956***	0.0782**
	(0.0200)	(0.0392)	(0.0226)	(0.0218)	(0.0392)
ATT (t+5)	0.0412	0.2087***	0.0968***	0.0962***	0.0958
	(0.0313)	(0.0690)	(0.0364)	(0.0335)	(0.0694)
ATT (average)	0.0289***	0.0490***	0.0304***	0.0336***	0.0301**
	(0.0084)	(0.0139)	(0.0091)	(0.0089)	(0.0139)
Test on pre-trend (Chi sq.)	16.0808	13.2067	12.2018	14.5930	8.0094
p-value	0.0973	0.2123	0.2718	0.1476	0.6279
N. of observations	28,282	27,157	27,157	27,157	27,157

Note. Standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are obtained using several difference-in-differences estimators. The doubly robust estimators, proposed by Sant'Anna and Zhao (2020), include a version based on stabilized inverse probability weighting and OLS (presented both without and with covariate matching), as well as an improved version that combines inverse probability of tilting and weighted least squares for enhanced efficiency. The outcome regression estimator uses OLS and, when no covariates are included, coincides with the standard two-way fixed effects DiD. The inverse probability weighting estimator with stabilized weights relies solely on propensity score weighting without regression adjustment.

Table C.2: Total expenditure (never treated)

	Doubly robust DiD based on stabilized inv. prob. weighting and OLS (no matching)	Doubly robust DiD based on stabilized inv. prob. weighting and OLS (with matching)	Improved doubly robust DiD estimator based on inv. prob. of tilting and weighted least squares	Outcome regression DiD estimator based on OLS	Inverse probability weighting DiD estimator with stabilized weights
ATT (t-4)	0.0080	0.0192	0.0131	0.0063	0.0132
	(0.0190)	(0.0374)	(0.0206)	(0.0196)	(0.0375)
ATT (t-3)	0.0001	-0.0173	-0.0129	-0.0124	-0.0120
	(0.0115)	(0.0178)	(0.0132)	(0.0124)	(0.0178)
ATT (t-2)	-0.0058	-0.0014	-0.0061	-0.0052	-0.0045
	(0.0080)	(0.0101)	(0.0085)	(0.0083)	(0.0102)
ATT (t-1)	0.0109	-0.0020	-0.0011	-0.0014	-0.0014
	(0.0072)	(0.0093)	(0.0077)	(0.0075)	(0.0093)
ATT (t)	0.0053	0.0145	0.0082	0.0083	0.0078
	(0.0072)	(0.0107)	(0.0079)	(0.0078)	(0.0107)
ATT (t+1)	0.0243***	0.0220*	0.0182*	0.0193**	0.0178
	(0.0086)	(0.0122)	(0.0093)	(0.0092)	(0.0122)
ATT (t+2)	0.0385***	0.0285**	0.0214*	0.0263**	0.0216
	(0.0105)	(0.0133)	(0.0111)	(0.0109)	(0.0133)
ATT (t+3)	0.0507***	0.0785***	0.0572***	0.0596***	0.0576***
	(0.0130)	(0.0190)	(0.0136)	(0.0134)	(0.0190)
ATT (t+4)	0.0426**	0.1411***	0.0781***	0.0956***	0.0782**
	(0.0200)	(0.0392)	(0.0226)	(0.0218)	(0.0392)
ATT (t+5)	0.0412	0.2087***	0.0968***	0.0962***	0.0958
	(0.0313)	(0.0690)	(0.0364)	(0.0335)	(0.0694)
ATT (average)	0.0296***	0.0485***	0.0312***	0.0343***	0.0311**
	(0.0084)	(0.0135)	(0.0091)	(0.0089)	(0.0135)
Test on pre-trend (Chi sq.)	16.0813	12.4533	11.9447	14.8874	7.7128
p-value	0.0973	0.2559	0.2888	0.1362	0.6569
N. of observations	28,272	27,147	27,147	27,147	27,147

Note. Standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are obtained using several difference-in-differences estimators. The doubly robust estimators, proposed by Sant'Anna and Zhao (2020), include a version based on stabilized inverse probability weighting and OLS (presented both without and with covariate matching), as well as an improved version that combines inverse probability of tilting and weighted least squares for enhanced efficiency. The outcome regression estimator uses OLS and, when no covariates are included, coincides with the standard two-way fixed effects DiD. The inverse probability weighting estimator with stabilized weights relies solely on propensity score weighting without regression adjustment.

Table C.3: Total revenue (not yet treated)

	Doubly robust DiD based on inv. prob. and weighted least squares (no matching)	Doubly robust DiD based on inv. prob. and weighted least squares (with matching)	Doubly robust DiD based on stabilized inverse probability weighting and OLS	Outcome regression DiD estimator based on OLS	Inverse probability weighting DiD estimator with stabilized weights
ATT (t-4)	0.0012	-0.0011	0.0078	-0.0085	0.0074
	(0.0188)	(0.0369)	(0.0201)	(0.0195)	(0.0369)
ATT (t-3)	0.0085	-0.0005	-0.0014	0.0039	0.0000
	(0.0122)	(0.0185)	(0.0140)	(0.0130)	(0.0186)
ATT (t-2)	0.0050	0.0160	0.0069	0.0072	0.0084
	(0.0076)	(0.0098)	(0.0083)	(0.0080)	(0.0098)
ATT (t-1)	-0.0009	-0.0169	-0.0104	-0.0096	-0.0108
	(0.0072)	(0.0093)	(0.0078)	(0.0076)	(0.0093)
ATT (t)	0.0079	0.0241**	0.0149*	0.0152*	0.0142
	(0.0074)	(0.0112)	(0.0079)	(0.0078)	(0.0112)
ATT (t+1)	0.0472***	0.0447***	0.0336***	0.0374***	0.0325***
	(0.0084)	(0.0124)	(0.0090)	(0.0089)	(0.0125)
ATT (t+2)	0.0529***	0.0500***	0.0404***	0.0433***	0.0400***
	(0.0104)	(0.0134)	(0.0108)	(0.0107)	(0.0135)
ATT (t+3)	0.0497***	0.0834***	0.0566***	0.0623***	0.0570***
	(0.0127)	(0.0186)	(0.0132)	(0.0130)	(0.0185)
ATT (t+4)	0.0220	0.0985***	0.0568***	0.0760***	0.0568
	(0.0195)	(0.0376)	(0.0219)	(0.0212)	(0.0376)
ATT (t+5)	0.0316	0.1800***	0.0846**	0.0823***	0.0838
	(0.0295)	(0.0646)	(0.0340)	(0.0320)	(0.0649)
ATT (average)	0.0368***	0.0576***	0.0386***	0.0425***	0.0381***
	(0.0082)	(0.0131)	(0.0087)	(0.0085)	(0.0131)
Test on pre-trend (Chi sq.)	17.4077	17.6376	14.8373	18.5653	6.6558
p-value	0.0658	0.0614	0.1381	0.0461	0.7575
N. of observations	28,289	27,164	27,164	27,164	27,164

Note. Standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are obtained using several difference-in-differences estimators. The doubly robust estimators, proposed by Sant'Anna and Zhao (2020), include a version based on stabilized inverse probability weighting and OLS (presented both without and with covariate matching), as well as an improved version that combines inverse probability of tilting and weighted least squares for enhanced efficiency. The outcome regression estimator uses OLS and, when no covariates are included, coincides with the standard two-way fixed effects DiD. The inverse probability weighting estimator with stabilized weights relies solely on propensity score weighting without regression adjustment.

Table C.4: Total revenue (never treated)

	Doubly robust DiD based on inv. prob. and weighted least squares (no matching)	Doubly robust DiD based on inv. prob. and weighted least squares (with matching)	Doubly robust DiD based on stabilized inverse probability weighting and OLS	Outcome regression DiD estimator based on OLS	Inverse probability weighting DiD estimator with stabilized weights
ATT (t-4)	0.0012	-0.0011	0.0078	-0.0085	0.0074
	(0.0188)	(0.0369)	(0.0201)	(0.0195)	(0.0369)
ATT (t-3)	0.0085	-0.0012	-0.0020	0.0042	-0.0009
	(0.0121)	(0.0182)	(0.0136)	(0.0128)	(0.0182)
ATT (t-2)	0.0061	0.0168*	0.0075	0.0071	0.0094
	(0.0076)	(0.0099)	(0.0083)	(0.0080)	(0.0099)
ATT (t-1)	-0.0015	-0.0153	-0.0091	-0.0097	-0.0093
	(0.0072)	(0.0093)	(0.0077)	(0.0075)	(0.0092)
ATT (t)	0.0095	0.0219**	0.0150*	0.0160**	0.0143
	(0.0073)	(0.0106)	(0.0079)	(0.0078)	(0.0106)
ATT (t+1)	0.0475***	0.0460***	0.0356***	0.0384***	0.0347***
	(0.0084)	(0.0118)	(0.0089)	(0.0088)	(0.0118)
ATT (t+2)	0.0536***	0.0493***	0.0407***	0.0438***	0.0404***
	(0.0105)	(0.0131)	(0.0108)	(0.0107)	(0.0131)
ATT (t+3)	0.0496***	0.0807***	0.0566***	0.0620***	0.0570***
	(0.0127)	(0.0181)	(0.0132)	(0.0130)	(0.0180)
ATT (t+4)	0.0220	0.0985***	0.0568***	0.0760***	0.0568
	(0.0195)	(0.0376)	(0.0219)	(0.0212)	(0.0376)
ATT (t+5)	0.0316	0.1800***	0.0846**	0.0823***	0.0838
	(0.0295)	(0.0646)	(0.0340)	(0.0320)	(0.0649)
ATT (average)	0.0374***	0.0567***	0.0392***	0.0430***	0.0387***
	(0.0082)	(0.0127)	(0.0087)	(0.0086)	(0.0127)
Test on pre-trend (Chi sq.)	17.4065	17.7803	14.9057	18.9188	6.9159
p-value	0.0658	0.0588	0.1355	0.0413	0.7334
N. of observations	28,279	27,154	27,154	27,154	27,154

Note. Standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are obtained using several difference-in-differences estimators. The doubly robust estimators, proposed by Sant'Anna and Zhao (2020), include a version based on stabilized inverse probability weighting and OLS (presented both without and with covariate matching), as well as an improved version that combines inverse probability of tilting and weighted least squares for enhanced efficiency. The outcome regression estimator uses OLS and, when no covariates are included, coincides with the standard two-way fixed effects DiD. The inverse probability weighting estimator with stabilized weights relies solely on propensity score weighting without regression adjustment.

Table C.5: Current expenditure (not yet treated)

	Doubly robust DiD based on inv. prob. and weighted least squares (no matching)	Doubly robust DiD based on inv. prob. and weighted least squares (with matching)	Doubly robust DiD based on stabilized inverse probability weighting and OLS	Outcome regression DiD estimator based on OLS	Inverse probability weighting DiD estimator with stabilized weights
ATT (t-4)	-0.0081	0.0134	0.0110	0.0029	0.0106
	(0.0069)	(0.0147)	(0.0095)	(0.0078)	(0.0148)
ATT (t-3)	-0.0160	-0.0161	-0.0097	-0.0086	-0.0097
	(0.0051)	(0.0077)	(0.0054)	(0.0053)	(0.0076)
ATT (t-2)	-0.0057	-0.0059	-0.0055	-0.0065	-0.0051
	(0.0031)	(0.0040)	(0.0034)	(0.0034)	(0.0040)
ATT (t-1)	-0.0012	-0.0023	-0.0011	-0.0007	-0.0012
	(0.0028)	(0.0035)	(0.0030)	(0.0029)	(0.0035)
ATT (t)	-0.0042	-0.0049	-0.0026	-0.0030	-0.0027
	(0.0029)	(0.0045)	(0.0032)	(0.0031)	(0.0045)
ATT (t+1)	0.0078**	-0.0004	0.0036	0.0033	0.0036
	(0.0035)	(0.0051)	(0.0038)	(0.0037)	(0.0051)
ATT (t+2)	0.0074*	-0.0007	0.0017	0.0035	0.0017
	(0.0045)	(0.0063)	(0.0048)	(0.0048)	(0.0063)
ATT (t+3)	0.0174***	0.0162*	0.0111**	0.0136**	0.0107
	(0.0053)	(0.0085)	(0.0056)	(0.0056)	(0.0085)
ATT (t+4)	0.0299***	0.0245	0.0180*	0.0241**	0.0183
	(0.0091)	(0.0177)	(0.0101)	(0.0099)	(0.0178)
ATT (t+5)	0.0115	0.0074	-0.0004	0.0071	-0.0016
	(0.0139)	(0.0313)	(0.0159)	(0.0154)	(0.0314)
ATT (average)	0.0084**	0.0036	0.0039	0.0054	0.0038
	(0.0037)	(0.0061)	(0.0039)	(0.0039)	(0.0062)
Test on pre-trend (Chi sq.)	31.0512	21.3031	21.1322	20.6585	12.8803
p-value	0.0006	0.0191	0.0202	0.0236	0.2304
N. of observations	28,289	27,164	27,164	27,164	27,164

Note. Standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are obtained using several difference-in-differences estimators. The doubly robust estimators, proposed by Sant'Anna and Zhao (2020), include a version based on stabilized inverse probability weighting and OLS (presented both without and with covariate matching), as well as an improved version that combines inverse probability of tilting and weighted least squares for enhanced efficiency. The outcome regression estimator uses OLS and, when no covariates are included, coincides with the standard two-way fixed effects DiD. The inverse probability weighting estimator with stabilized weights relies solely on propensity score weighting without regression adjustment.

Table C.6: Current expenditure (never treated)

	Doubly robust DiD based on inv. prob. and weighted least squares (no matching)	Doubly robust DiD based on inv. prob. and weighted least squares (with matching)	Doubly robust DiD based on stabilized inverse probability weighting and OLS	Outcome regression DiD estimator based on OLS	Inverse probability weighting DiD estimator with stabilized weights
ATT (t-4)	-0.0081	0.0134	0.0110	0.0029	0.0106
	(0.0069)	(0.0147)	(0.0095)	(0.0078)	(0.0148)
ATT (t-3)	-0.0162	-0.0157	-0.0094	-0.0087	-0.0093
	(0.0051)	(0.0077)	(0.0054)	(0.0054)	(0.0076)
ATT (t-2)	-0.0067	-0.0061	-0.0058	-0.0068	-0.0053
	(0.0031)	(0.0040)	(0.0034)	(0.0034)	(0.0040)
ATT (t-1)	-0.0023	-0.0030	-0.0016	-0.0015	-0.0017
	(0.0028)	(0.0035)	(0.0031)	(0.0029)	(0.0035)
ATT (t)	-0.0048	-0.0047	-0.0029	-0.0031	-0.0030
	(0.0029)	(0.0043)	(0.0032)	(0.0031)	(0.0044)
ATT (t+1)	0.0068*	0.0005	0.0037	0.0034	0.0037
	(0.0035)	(0.0049)	(0.0038)	(0.0037)	(0.0049)
ATT (t+2)	0.0068	-0.0008	0.0014	0.0032	0.0014
	(0.0045)	(0.0061)	(0.0048)	(0.0047)	(0.0061)
ATT (t+3)	0.0168***	0.0157*	0.0111**	0.0135**	0.0107
	(0.0053)	(0.0082)	(0.0056)	(0.0056)	(0.0082)
ATT (t+4)	0.0299***	0.0245	0.0180*	0.0241**	0.0183
	(0.0091)	(0.0177)	(0.0101)	(0.0099)	(0.0178)
ATT (t+5)	0.0115	0.0074	-0.0004	0.0071	-0.0016
	(0.0139)	(0.0313)	(0.0159)	(0.0154)	(0.0314)
ATT (average)	0.0078**	0.0038	0.0038	0.0053	0.0037
	(0.0037)	(0.0060)	(0.0039)	(0.0039)	(0.0060)
Test on pre-trend (Chi sq.)	31.0535	24.0023	24.1475	22.1229	14.6417
p-value	0.0006	0.0076	0.0072	0.0145	0.1457
N. of observations	28,279	27,154	27,154	27,154	27,154

Note. Standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are obtained using several difference-in-differences estimators. The doubly robust estimators, proposed by Sant'Anna and Zhao (2020), include a version based on stabilized inverse probability weighting and OLS (presented both without and with covariate matching), as well as an improved version that combines inverse probability of tilting and weighted least squares for enhanced efficiency. The outcome regression estimator uses OLS and, when no covariates are included, coincides with the standard two-way fixed effects DiD. The inverse probability weighting estimator with stabilized weights relies solely on propensity score weighting without regression adjustment.

Table C.7: Capital expenditure (not yet treated)

	Doubly robust DiD based on inv. prob. and weighted least squares (no matching)	Doubly robust DiD based on inv. prob. and weighted least squares (with matching)	Doubly robust DiD based on stabilized inverse probability weighting and OLS	Outcome regression DiD estimator based on OLS	Inverse probability weighting DiD estimator with stabilized weights
ATT (t-4)	0.0042	-0.0509	-0.0278	-0.0221	-0.0290
	(0.0971)	(0.1988)	(0.1080)	(0.1042)	(0.1986)
ATT (t-3)	0.0549	-0.1060	-0.0838	-0.0836	-0.0857
	(0.0664)	(0.1046)	(0.0727)	(0.0710)	(0.1046)
ATT (t-2)	-0.0398	-0.0038	-0.0410	-0.0311	-0.0389
	(0.0412)	(0.0502)	(0.0435)	(0.0433)	(0.0501)
ATT (t-1)	0.0379	0.0309	0.0282	0.0226	0.0276
	(0.0353)	(0.0433)	(0.0377)	(0.0372)	(0.0434)
ATT (t)	0.0173	0.0505	0.0112	0.0115	0.0084
	(0.0307)	(0.0465)	(0.0330)	(0.0325)	(0.0464)
ATT (t+1)	0.0190	0.0658	0.0273	0.0309	0.0270
	(0.0324)	(0.0480)	(0.0352)	(0.0346)	(0.0478)
ATT (t+2)	0.0728**	0.1189***	0.0685*	0.0756**	0.0717
	(0.0358)	(0.0454)	(0.0377)	(0.0374)	(0.0452)
ATT (t+3)	0.1095**	0.2702***	0.1568***	0.1511***	0.1575**
	(0.0428)	(0.0638)	(0.0449)	(0.0443)	(0.0632)
ATT (t+4)	-0.0224	0.4557***	0.2021***	0.2309***	0.2045*
	(0.0622)	(0.1209)	(0.0685)	(0.0667)	(0.1197)
ATT (t+5)	0.2598***	0.8493***	0.4032***	0.3880***	0.4045**
	(0.0906)	(0.1939)	(0.1014)	(0.0957)	(0.1943)
ATT (average)	0.0534*	0.1728***	0.0846***	0.0876***	0.0849*
	(0.0305)	(0.0484)	(0.0324)	(0.0318)	(0.0477)
Test on pre-trend (Chi sq.)	12.1409	15.8831	11.5712	18.3702	7.6850
p-value	0.2757	0.1030	0.3148	0.0490	0.6596
N. of observations	28,189	27,065	27,065	27,065	27,065

Note. Standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are obtained using several difference-in-differences estimators. The doubly robust estimators, proposed by Sant'Anna and Zhao (2020), include a version based on stabilized inverse probability weighting and OLS (presented both without and with covariate matching), as well as an improved version that combines inverse probability of tilting and weighted least squares for enhanced efficiency. The outcome regression estimator uses OLS and, when no covariates are included, coincides with the standard two-way fixed effects DiD. The inverse probability weighting estimator with stabilized weights relies solely on propensity score weighting without regression adjustment.

Table C.8: Capital expenditure (never treated)

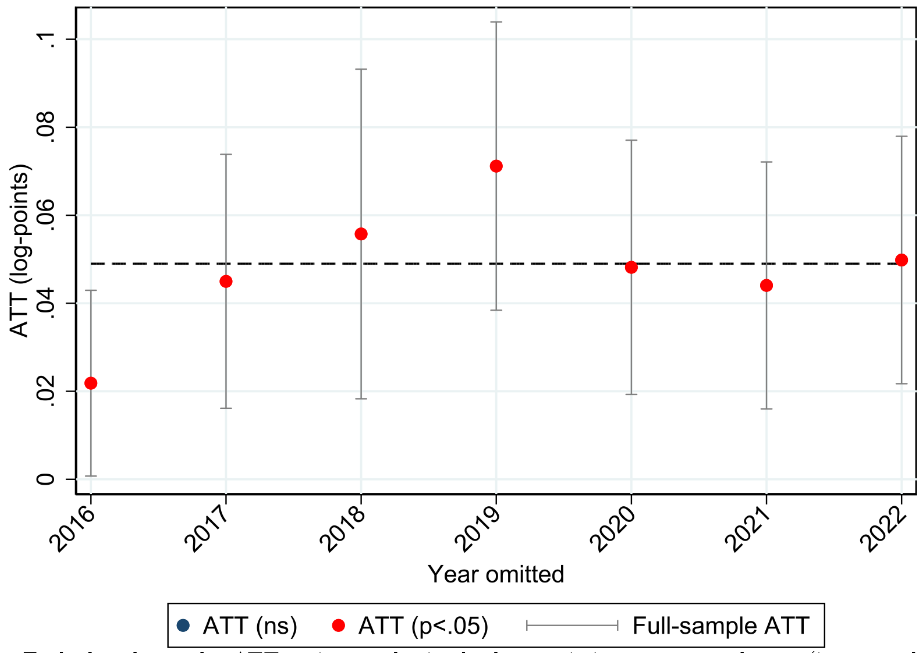
	Doubly robust DiD based on inv. prob. and weighted least squares (no matching)	Doubly robust DiD based on inv. prob. and weighted least squares (with matching)	Improved doubly robust DiD estimator (inv. prob. of tilting & WLS)	Outcome regression DiD estimator based on OLS	Inverse probability weighting DiD estimator with stabilized weights
ATT (t-4)	0.0042	-0.0509	-0.0278	-0.0221	-0.0290
	(0.0971)	(0.1988)	(0.1080)	(0.1042)	(0.1986)
ATT (t-3)	0.0550	-0.1050	-0.0838	-0.0910	-0.0834
	(0.0657)	(0.1050)	(0.0728)	(0.0704)	(0.1050)
ATT (t-2)	-0.0362	-0.0112	-0.0493	-0.0432	-0.0457
	(0.0405)	(0.0493)	(0.0427)	(0.0424)	(0.0492)
ATT (t-1)	0.0368	0.0198	0.0182	0.0105	0.0167
	(0.0342)	(0.0425)	(0.0369)	(0.0364)	(0.0427)
ATT (t)	0.0228	0.0123	0.0380	0.0144	0.0100
	(0.0302)	(0.0329)	(0.0435)	(0.0324)	(0.0435)
ATT (t+1)	0.0240	0.0331	0.0626	0.0395	0.0332
	(0.0318)	(0.0346)	(0.0448)	(0.0339)	(0.0447)
ATT (t+2)	0.0794**	0.1188***	0.0720*	0.0806**	0.0756*
	(0.0358)	(0.0444)	(0.0377)	(0.0374)	(0.0442)
ATT (t+3)	0.1120***	0.2613***	0.1568***	0.1520***	0.1575**
	(0.0429)	(0.0618)	(0.0449)	(0.0444)	(0.0613)
ATT (t+4)	-0.0224	0.4557***	0.2021***	0.2309***	0.2045*
	(0.0622)	(0.1209)	(0.0685)	(0.0667)	(0.1197)
ATT (t+5)	0.2598***	0.8493***	0.4032***	0.3880***	0.4045**
	(0.0906)	(0.1939)	(0.1014)	(0.0957)	(0.1943)
ATT (average)	0.0578*	0.1674***	0.0871***	0.0917***	0.0877*
	(0.0303)	(0.0466)	(0.0324)	(0.0317)	(0.0460)
Test on pre-trend (Chi sq.)	12.1411	15.4578	11.4202	18.8898	7.6633
p-value	0.2757	0.1162	0.3257	0.0417	0.6617
N. of observations	28,175	27,051	27,051	27,051	27,051

Note. Standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are obtained using several difference-in-differences estimators. The doubly robust estimators, proposed by Sant'Anna and Zhao (2020), include a version based on stabilized inverse probability weighting and OLS (presented both without and with covariate matching), as well as an improved version that combines inverse probability of tilting and weighted least squares for enhanced efficiency. The outcome regression estimator uses OLS and, when no covariates are included, coincides with the standard two-way fixed effects DiD. The inverse probability weighting estimator with stabilized weights relies solely on propensity score weighting without regression adjustment.

C.2 Jackknife

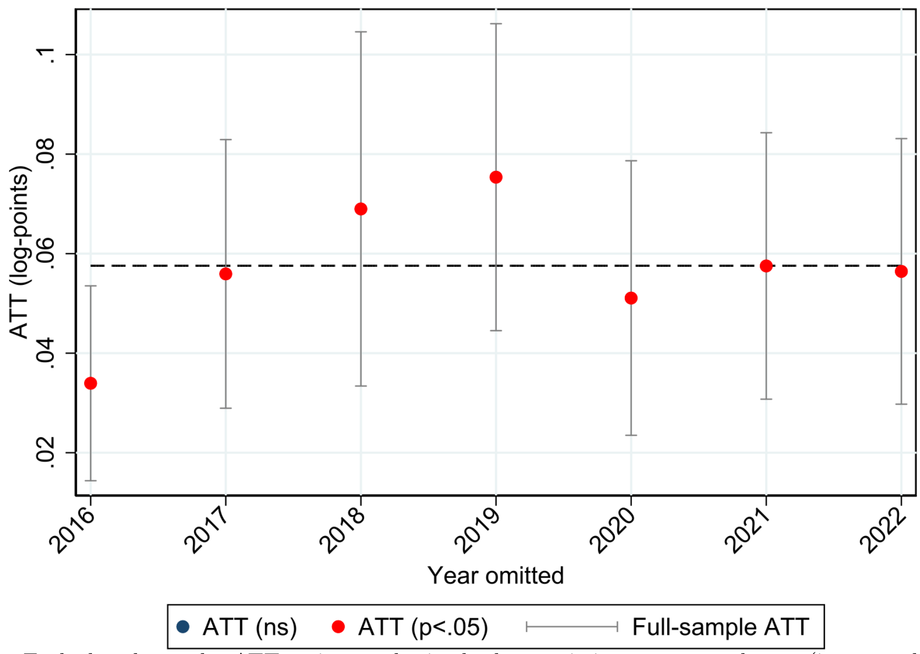
C.2.1 Event-based

Figure C.1: Event-based jackknife sensitivity: total expenditure



Note. Each dot shows the ATT estimate obtained when omitting one treated year (i.e., one disaster event) from the estimation sample. Vertical bars denote 95% confidence intervals. The dashed line marks the full-sample ATT estimate. Red dots indicate statistically significant ($p < 0.05$) ATT estimates.

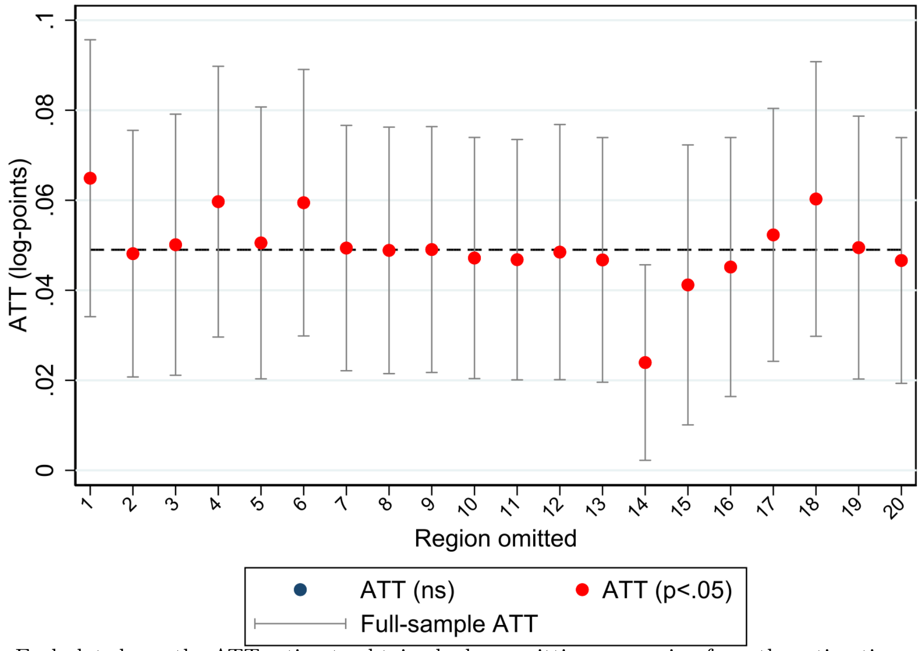
Figure C.2: Event-based jackknife sensitivity: total revenue



Note. Each dot shows the ATT estimate obtained when omitting one treated year (i.e., one disaster event) from the estimation sample. Vertical bars denote 95% confidence intervals. The dashed line marks the full-sample ATT estimate. Red dots indicate statistically significant ($p < 0.05$) ATT estimates.

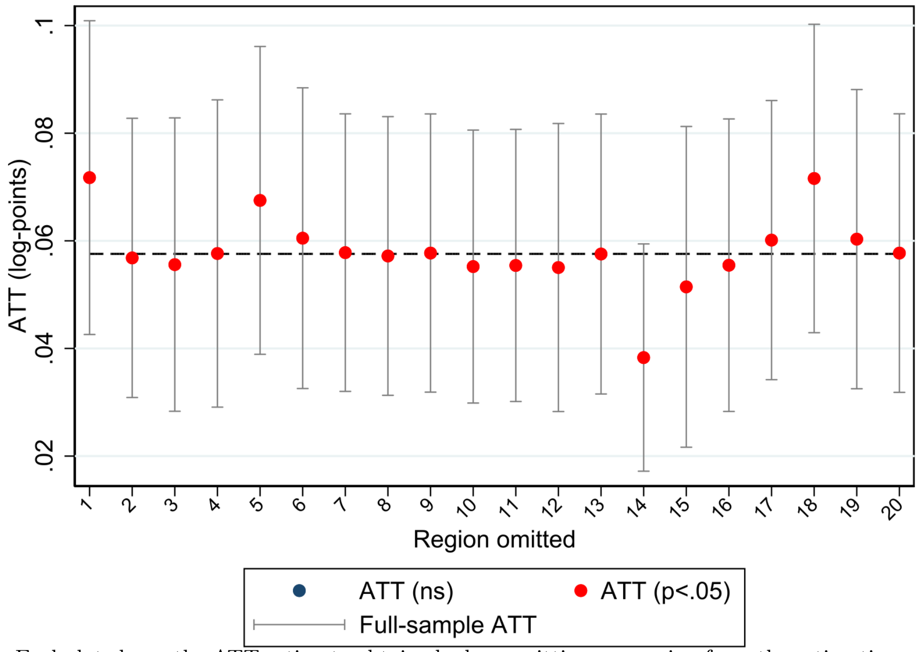
C.2.2 Region-based

Figure C.3: Region-based sensitivity: total expenditure



Note. Each dot shows the ATT estimate obtained when omitting one region from the estimation sample. Vertical bars denote 95% confidence intervals. The dashed line marks the full-sample ATT estimate. Red dots indicate statistically significant (p < 0.05) ATT estimates.

Figure C.4: Region-based sensitivity: total revenue

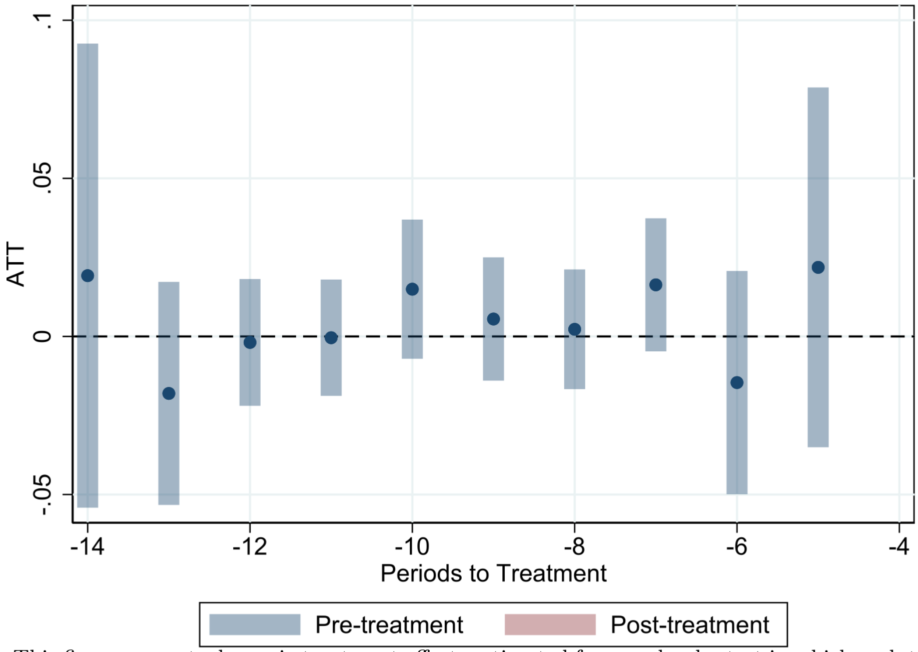


Note. Each dot shows the ATT estimate obtained when omitting one region from the estimation sample. Vertical bars denote 95% confidence intervals. The dashed line marks the full-sample ATT estimate. Red dots indicate statistically significant (p < 0.05) ATT estimates.

C.3 Placebo

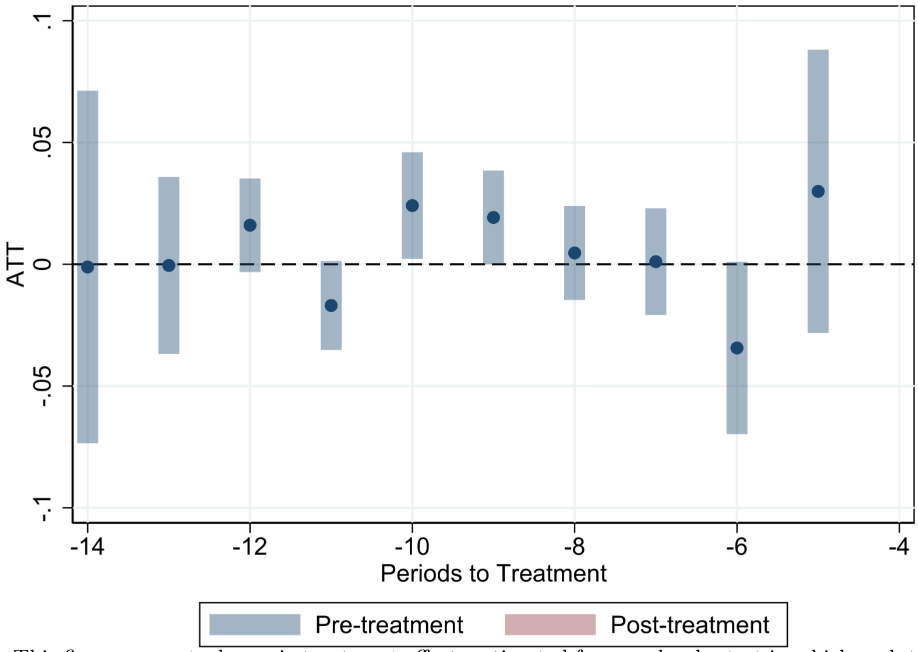
C.3.1 Post-treatment window

Figure C.5: Post-treatment window: total expenditure



Note. This figure presents dynamic treatment effects estimated from a placebo test in which each treated municipality is randomly assigned a treatment year between 2017 and 2021. These assigned years differ from the actual treatment years, and no real treatment occurs during the assigned period. Point estimates and 95% confidence intervals are displayed. The dashed line indicates zero effect.

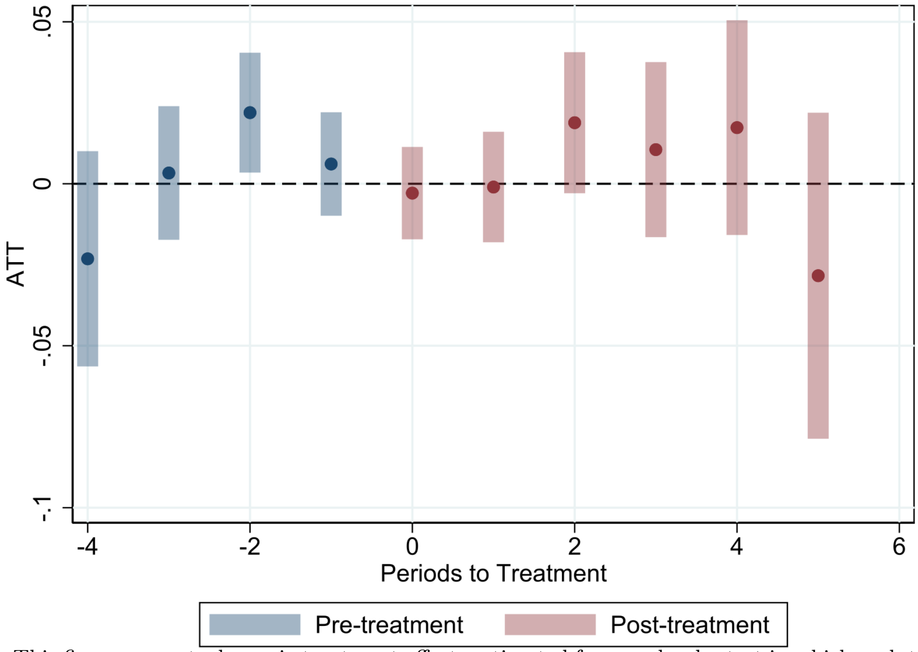
Figure C.6: Post-treatment window: total revenue



Note. This figure presents dynamic treatment effects estimated from a placebo test in which each treated municipality is randomly assigned a treatment year between 2017 and 2021. These assigned years differ from the actual treatment years, and no real treatment occurs during the assigned period. Point estimates and 95% confidence intervals are displayed. The dashed line indicates zero effect.

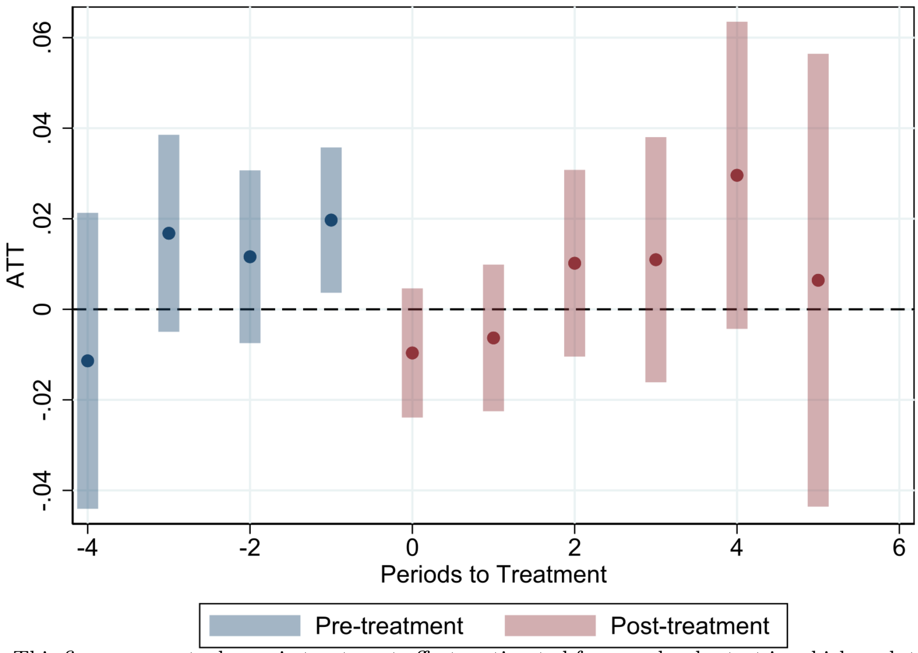
C.3.2 Random-year treatment

Figure C.7: Random-year placebo: total expenditure



Note. This figure presents dynamic treatment effects estimated from a placebo test in which each treated municipality is randomly assigned a treatment year between 2017 and 2021. No actual treatment occurs during this period. Point estimates and 95% confidence intervals are displayed. The dashed line indicates zero effect.

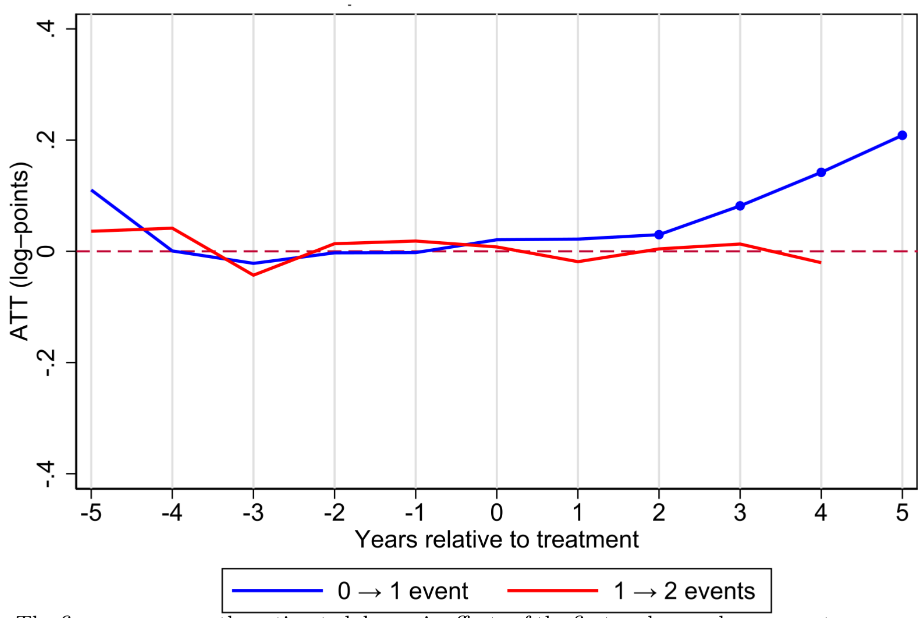
Figure C.8: Random-year placebo: total revenue



Note. This figure presents dynamic treatment effects estimated from a placebo test in which each treated municipality is randomly assigned a treatment year between 2017 and 2021. No actual treatment occurs during this period. Point estimates and 95% confidence intervals are displayed. The dashed line indicates zero effect.

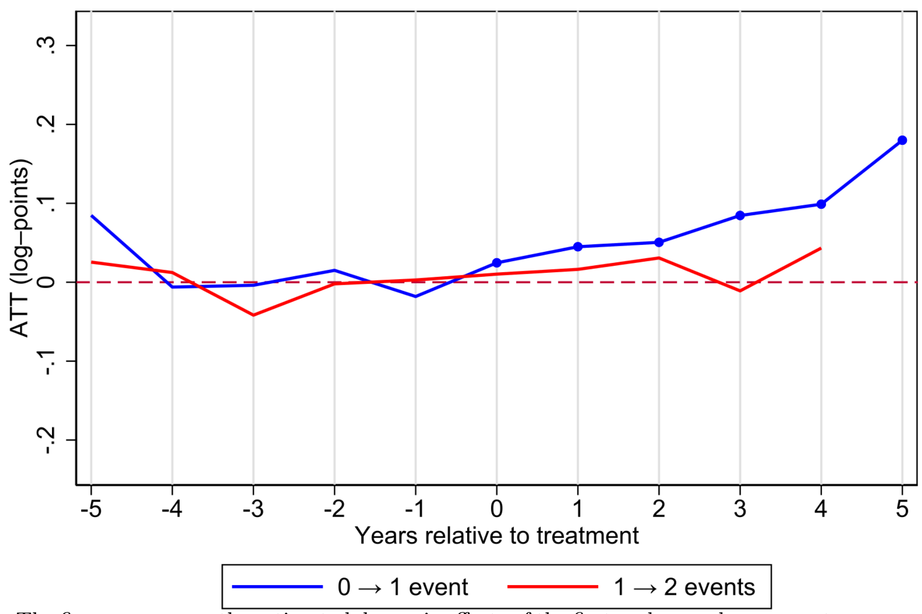
C.4 Robustness by exposure frequency: single vs. multiple events

Figure C.9: First vs. second hit on Total expenditure (not-yet treated)



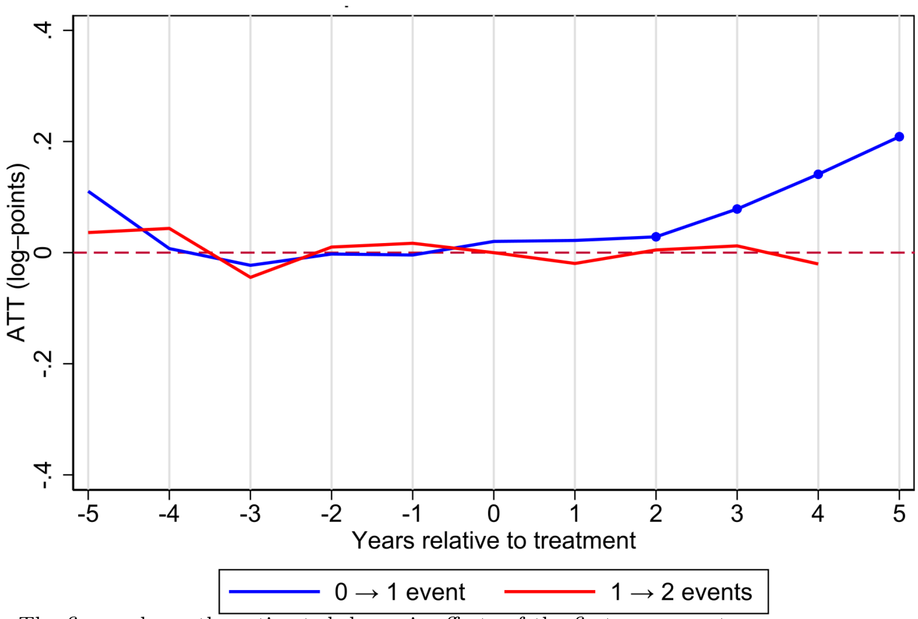
Note. The figure compares the estimated dynamic effects of the first and second exposure to an emergency event on total municipal expenditure. Estimates are obtained using the doubly robust inverse probability weighting estimator, with not-yet-treated municipalities used as the control group.

Figure C.10: First vs. second hit on Total revenue (not-yet treated)



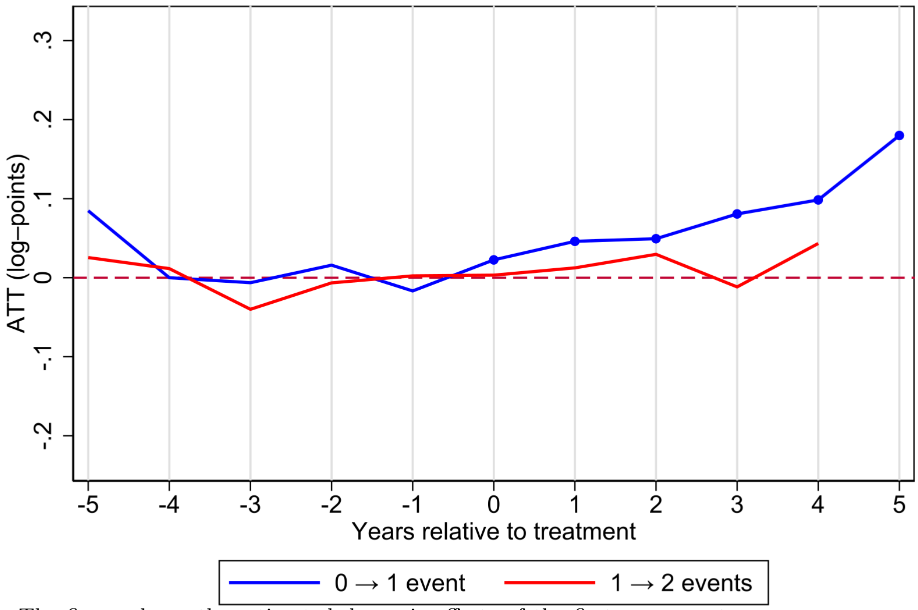
Note. The figure compares the estimated dynamic effects of the first and second exposure to an emergency event on total municipal revenue. Estimates are obtained using the doubly robust inverse probability weighting estimator, with not-yet-treated municipalities used as the control group.

Figure C.11: First vs. second hit on Total expenditure (never treated)



Note. The figure shows the estimated dynamic effects of the first exposure to an emergency event on total municipal expenditure. Estimates are obtained using the doubly robust inverse probability weighting estimator, with never-treated municipalities used as the control group.

Figure C.12: First vs. second hit on Total revenue (never treated)



Note. The figure shows the estimated dynamic effects of the first exposure to an emergency event on total municipal revenue. Estimates are obtained using the doubly robust inverse probability weighting estimator, with never-treated municipalities used as the control group.

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